6D-1

Monthly Revenue Growth and Cross-Sectional Stock Returns

Weifeng Hung
Department of Finance
Feng Chia University, Taiwan
wfhung@fcu.edu.tw

Chia-Chi Lu
Graduate Institute of Accounting and Department of Finance
National Central University, Taiwan
lunina@ncu.edu.tw

J. Jimmy Yang
School of Accounting, Finance, and Information Systems
College of Business
Oregon State University
jimmy.yang@bus.oregonstate.edu.

Weifeng Hung acknowledges the research grants (MOST 110-2410-H-035-016) from the Ministry of Science and Technology in Taiwan.

Current version June 2023

Abstract

With a unique dataset of monthly operating revenue in Taiwan, we document significantly positive post-revenues-announcement drift (PRAD), i.e., stocks with high revenue growth (RG) earn higher future returns than stocks with low RG. The monthly equal-weighted and value-weighted Fama-French three-factor alphas are 1.09% and 1.00%, respectively. The PRAD is robust to size, price-to-book ratio, beta, turnover ratio, momentum, short-term reversals, illiquidity, idiosyncratic volatility, sub-period tests, and post-earnings-announcement drift. We employ RG persistence as a measure for newly announced revenue information and find that the persistence level plays a substantial role in the PRAD. Furthermore, we observe that investors underreact to the possibilities of RG persistence, especially for stocks trading near their 52-week highs.

Keywords: PRAD, monthly revenue growth, persistence, momentum

1. Introduction

TSMC revenue hits second consecutive record high

Taiwan Semiconductor Manufacturing Co (TSMC), a supplier to Apple Inc, yesterday reported a record high revenue of NT$127.59 billion (US$4.4 billion) for last month, up 3.8 percent month-on-month and 24.9 percent year-on-year.[1]

-Taipei Times 2020/10/09

In addition to earnings,[2] revenue has been proven to impact stock returns significantly. For instance, Jegadeesh and Livnat (2006) document significant abnormal returns in the post-announcement period for stocks that experience large revenue growth. Chen et al. (2014) indicate that revenue surprises carry exclusive unpriced information content. However, the most frequent financial reports available are quarterly. Because quarterly financial reports aggregate three months' aggregate information, any exogenous shocks occurring within the quarter cannot be easily detected through the quarterly financial statements. Further, the time between the end of the calendar quarter and the date of filing the report is too long to determine whether the market is surprised or affected by other news.[3] Therefore, it is advantageous to use higher-frequency data, if available, to examine how investors respond to financial announcements regarding the top-line performance.

Unlike most countries where quarterly financial reports are the norm, Taiwan is the only market that requires publicly-traded firms to announce operating revenue for the

---

[1]Link: https://www.taipeitimes.com/News/biz/archives/2020/10/09/2003744834.

[2]Post-earnings-announcement drift (PEAD) has been documented to challenge the view that security prices immediately reflect all publicly available information (Ball and Brown (1968), Bernard and Thomas (1989), Chan et al. (1996), and Fama (1998)).

[3]Specifically, for the first three quarters of a calendar year, the Taiwan Stock Exchange Corporation (TWSE) requires companies to file quarterly earnings reports no later than 45 days after the end of calendar quarter (i.e., 15th May, 14th August, 14th November, for Q1, Q2, and Q3, respectively), and the companies are required to file the fourth quarter (Q4) earnings no later than three months after the end of the fiscal year (31st March of next year).

preceding month by the 10th day of each calendar month. Using such unique interim data, i.e., monthly revenue, we can partially mitigate the problem of insufficient information prior to earnings report and examine whether the market incorporates the interim information into the stock price.[4]

In this paper, we define revenue growth (RG) as the monthly growth rate of operating revenue from the same calendar month of the previous year. We use the year-over-year monthly revenue growth rate because it is the measurement disclosed in the mainstream financial news. It is thus straightforward to use the measure to examine how investors respond to the required monthly firm disclosure on the top-line performance. The post-revenues-announcement drift (PRAD) is calculated as the difference in the average monthly returns between firms in the top RG quintile and firms in the bottom RG quintile. We use PRAD to examine how the investors respond to the revenue announcements. The results are summarized as follows. First, we document significantly positive post-revenue-announcement drift (PRAD), i.e., the stocks with high revenue growth (RG) earn higher future returns than stocks with low revenue growth. The positive relation between RG and future stock returns indicates that the stocks with high RG tend to be underpriced, and stocks with low RG tend to be overpriced. The equally-weighted (value-weighted) Fama-French three-factor alpha is 1.09% (1.00%). The one dollar invested at the beginning of 1990 will earn about 39 dollars and 19 dollars after 30 years for equally-weighted and value-weighted portfolios, respectively.

Second, several studies document that stock return anomalies are caused by costs of arbitrage.[5] We use four measures to proxy for limits-to-arbitrage, including market

[4] The information about the rule of Article 3 is provided on the following website: http://eng.selaw.com.tw/LawArticle.aspx?LawID=FL007250&ModifyDate=1090930.

[5] Chordia et al. (2009) show that the post-earnings-announcement drift (PEAD) occurs mainly

capitalization (Brav et al. (2010)), illiquidity ((Chordia et al. (2009)), relative bid-ask spread (Ng et al. (2008)), and idiosyncratic volatility (Mendenhall (2004)). The evidence indicates that the PRAD is not driven by costly arbitrage, which is inconsistent with the results of PEAD (Chordia et al. (2009)). Further, the PRAD is not caused by many well-known variables capable of predicting cross-sectional stock returns, such as price-to-book ratio, beta, turnover ratio, momentum, and short-term reversals. The results are also robust to different sub-periods separating by January, the adoption of International Financial Reporting Standards (IFRS), investor sentiment, market return, and business cycles indicator. The results suggest that the RG might be another important characteristic in explaining stock returns in the Taiwan stock market.

To explore the source of PRAD, we apply the persistent rank metric to evaluate the impact of newly announced revenue information on the PRAD. The results show that the persistence in RG rank largely contributes to the positive PRAD. First, stocks with high RG are likely to have high RG in the next month. Compared to a randomly distributed percentage of 20%, around 57% (57%) of stocks in the top (bottom) RG portfolio continue to have the same rank in the following month. The evidence is consistent with Jegadeesh and Livnat (2006) that revenues tend to be persistent. Second, the overlapping PRAD returns quickly dissipate in the short term. With increasing holding months, the predictive power of old RG information on future RG information is decaying. In other words, with decreasing new RG information in the portfolio, the PRAD is deteriorating.

We use prior persistency to proxy for future persistency, i.e., newly announced

---

in highly illiquid stocks. They conclude that profits from the PEAD is not realizable because of trading frictions, i.e., high trading costs and high market impact costs. Ng et al. (2008) find that the PEAD strategy is significantly reduced after considering the impact of bid-ask spreads. Mendenhall (2004) indicates that stocks with high arbitrage risk, proxied by idiosyncratic volatility, exhibit more profits of PEAD than do stocks with low arbitrage risk.

revenue information. The persistent groups contain stocks with the same lagged one-period and lagged two-period ranks, while the non-persistent groups have stocks with different RG ranks. The results indicate that prior persistency can significantly improve the performance of PRAD. Further, the persistent PRAD significantly outperforms the non-persistent PRAD. The equally-weighted (value-weighted) risk-adjusted differences between persistent PRAD and non-persistent PRAD is 1.70% (1.63%) per month with t-statistics of 3.74 (2.96), suggesting that the prior RG persistency captures the PRAD. The evidence indicates that the newly announced revenue information significantly contributes to the PRAD, and prior persistence can effectively predict future revenue information.

However, if the stock has repeated its high RG in the past, why do investors not pay a high price for the stock with the high probability that the future RG will likely be high? Is the mispricing arising because of arbitrage limits or cognitive bias? In other words, we attempt to investigate whether the mispricing on high RG stocks is rational or not. Specifically, we examine why investors incorrectly evaluate the possibilities of future RG persistency. We use four arbitrage cost measures: market capitalization, illiquidity, relative bid-ask spread, and idiosyncratic volatility. In addition, three attention bias measures are adopted: the 52-week high ratio, recency ratio, and information discreteness.[6] The evidence suggests that the investor underreaction to the possibilities

[6]George and Hwang (2004) indicate that investors use the 52-week high (H52) as an anchor when assessing the stock price. Since investors pay too much attention to the anchor (anchoring bias), investors underreact to the positive (negative) news about the stocks whose prices are near (far from) their H52. For example, when good news in the prior year pushes a stock's closing price near a new H52, investors are reluctant to bid the price of the stock higher even if the information warrants it. As a result, they underreact to good news. When the information eventually prevails, and the price goes up, momentum occurs. Bhootra and Hur (2013) propose that anchoring bias is stronger for stocks with recent H52 than stocks with distant H52. According to Bhootra and Hur (2013), we construct a recency ratio (RR) to measure the distance to the past H52. Da et al. (2014) document that investors are inattentive to information arriving continuously in small amounts. A series of frequent gradual changes attracts less attention than infrequent dramatic changes. Following Da et al. (2014), we use the percentage

of RG persistency is significantly stronger for stocks with high 52-week than stocks with low 52-week. The results are consistent with the investor attention bias hypothesis rather than the arbitrage cost hypothesis. George et al. (2015) indicate that the underreaction to accounting fundamentals, such as earnings surprise, is associated with the anchoring on the 52-week high. Goh and Jeon (2017) observe that the post-earnings announcement drift (PEAD) effect is significantly more pronounced when stocks are nearing their 52-week highs, potentially influenced by the anchoring bias. Further, Byun et al. (2020) suggest that investors consider the 52-week high as the upper price limit and show that this psychological barrier affects their preferences for lottery-like stocks.[7] Consistent with prior studies, we show that the underreaction to the possibilities of future persistency is due to the anchoring on the 52-week high. That is, investors are reluctant to bid up the price of stocks trading near their 52-week high when the stocks have a high likelihood of persistence in RG.

Finally, DeFond et al. (2007) indicate that the market reaction to less frequent financial reporting, such as annual earnings announcements, is weaker when more frequent interim financial reporting is announced, indicating that earning information is more likely already impounded into the price. We test whether earnings information is already impounded into the price when the high-frequency data, i.e., revenue growth, is announced. If this is the case, the PRAD and PEAD should be dependent. The results show that the low-frequency announcement, i.e., PEAD, is not driven by the high-frequency announcements, i.e., PRAD, which is inconsistent with DeFond et al. (2007). On the other hand, PRAD still exists after controlling for earnings surprises. The

---

of positive daily returns relative negative daily returns to estimate information discreteness (ID) that captures the relative frequency of small signals.

[7]Tversky and Kahneman (1992) indicate that people have cognitive illusions regarding the probabilities. People tend to overweight small probabilities and underweight large probabilities.

evidence indicates that the information on quarterly earnings announcements and monthly revenue growth is different.

This paper contributes to the literature in several ways. First, we contribute to the literature by showing that high-frequency financial information, i.e., monthly revenue growth, is statistically and economically significant in predicting future stock returns. Second, we use the persistent rank metric to proxy for the newly announced revenue information and find that the predictive power of RG mainly comes from persistence in RG. That is, stocks with high RG have a high probability of having high RG in the future. Third, we show that the evaluation of possibilities of future revenue growth will be affected by 52-week high ratio. The investors underreact to the possibilities of RG persistence when the stock price is near the 52-week high. That is, the investors are anchored at the 52-week high price that they are not willing to bid up the price for the stocks with a high likelihood of having RG persistence.

This paper is structured as follows. Section 2 outlines the data used. Section 3 presents portfolio analyses of PRAD and assesses the impact of newly announced revenue information. Section 4 provides robustness checks and Section 5 concludes.

2. Data and variables definitions

We obtain our data, including the daily and monthly stock prices, market (TAIEX) returns (including dividends), other stock trading and accounting data, such as monthly operating revenues and the number of outstanding shares, from a commercial database maintained by the Taiwan Economic Journal (TEJ) from January 1990 until December 2020. The sample excludes stocks in the financial industry (TEJ first two digits SIC code = 28). Our key variable RG is defined as the monthly growth rate of operating revenue to the operating revenue with the same calendar month of the previous year.[8] By the 10th day of each calendar month, each listed firm is required to announce its operating revenue for the preceding month. The variables are explicitly defined in Appendix A.

Table 1 provides the descriptive statistics of firm characteristics used in this paper. The average RG of our sample is 12.63%, and the median RG is 2.84%, which shows that the RG distribution is right-skewed. Panel B shows that the RG has moderate correlations with other stock characteristics, with the highest being 0.19 between RG and the past 12-month return. The results suggest that because of the low correlation between RG and well-documented variables, such as market capitalization, price-to-book ratio, momentum, and illiquidity, the RG could be an essential factor to help explain stock returns in the Taiwan stock market.

[Table 1 here]

3. Post-revenues-announcement drift (PRAD)

3.1. Portfolio analysis

To avoid the look-ahead bias, for each stock at the end of month t, we sort all stocks into five groups based on RG in month t-1. The portfolios are held for one month in month t+1, and portfolio returns are equally and value-weighted. The PRAD is the difference in the average monthly returns between firms in the top RG quintile and those in the bottom RG quintile. Fama and French (1993) argue that investors require higher expected returns to hold risky stocks. Specifically, the outperformance of stocks with high RG may indicate they are more likely to be exposed to systematic risk. To

[8] To directly measure how investors react to the monthly announcement of operating revenue, we use a straightforward measure consistent with the one reported by the news, i.e., year-on-year (YoY) growth rate of operating revenue.

control for this possibility, we examine whether the RG effect can be explained by the following risk-based model proposed by Fama and French (1993):

$$r_{pt} = a_p + b_p MKT_t + s_p SMB_t + h_p HML_t + e_{pt}, \tag{1}$$

where $r_{p,t}$ is the raw return on portfolio p during month t, MKT_t is the excess monthly market return, SMB_t and HML_t are the monthly returns on the factor mimicking portfolios reflecting premiums on size and B/M effects, respectively, and a_p is the intercept term of the regression. Under the three-factor model, the intercept term a_p is frequently regarded as a measure of the abnormal return on portfolio p after controlling for the systematic risk factors.[9] The performances of the portfolios are measured by the raw returns and Fama-French (1993) alphas.

Panel A of Table 2 shows that the equally-weighted (value-weighted) PRAD (i.e., zero-investment portfolio raw returns between the high and low RG portfolios) of 1.035% (0.922%) is significantly positive. The corresponding equally-weighted (value-weighted) Fama-French three-factor alpha is 1.085% (1.000%). The results indicate that the correlation between revenue growth and future stock returns is significantly positive. That is, stocks with the highest RG tend to be underpriced, and stocks with the lowest RG tend to be overpriced. Further, the equally-weighted (value-weighted) returns of a zero-cost portfolio mainly come from the long leg of the portfolio, i.e., the high RG

[9] Following Fama and French (1993), HML and SMB are constructed as follows. At the beginning of each July from 1989 to 2020, all stocks are allocated to two size groups (small and big, S and B) based on whether their June market equity is below or above the median market equity. Then, all stocks are independently allocated to three BM groups (low, medium, and high; L, M, and H) based on the breakpoints for the bottom 30 percent, middle 40 percent, and top 30 percent of the values of BM. Six size/BM portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are constructed from the intersections of the two size and the three BM groups. The value-weighted returns on them are calculated from July to the next June, the first 12 months after formation. The portfolio return HML is the difference between the average returns on the S/H and the B/H portfolios and the average returns on the S/L and the B/L portfolios. Similarly, the SMB is the difference between the average returns on the S/L, S/M, and S/H portfolios and the average returns on the B/L, B/M, and B/H portfolios.

portfolio. Panel B of Table 2 presents the mean characteristics for the RG portfolios. Stocks with high RG tend to be associated with high market capitalization, high price-to-book ratio, high turnover, high beta, high idiosyncratic volatility, low illiquidity, low bid-ask spread, high prior-one month return, and high momentum. In the following sections, we will further explore whether returns of the RG portfolios are driven by those important variables.

Figure 1 shows that from January 1990 to December 2020, the buy-and-hold zero-cost returns on equally-weighted and value-weighted portfolios are higher than the index return on the Taiwan Stock Exchange. One dollar invested at the beginning of 1990 will earn about 39 dollars and 19 dollars after 30 years for equally-weighted and value-weighted portfolios, respectively.

[Table 2 here]

[Figure 1 here]

3.2. Cross-sectional regressions

We apply Fama-MacBeth cross-sectional regressions to test the relation between RG and future stock returns. The regressions include control variables that measure market capitalization, turnover ratio, price-to-book ratio, one-month prior returns (short-term reversal), and twelve-month prior returns (momentum), illiquidity, idiosyncratic volatility, bid-ask spread, and beta. For each month from January 1990 to December 2020, we cross-sectionally regress returns on independent variables by OLS. The time-series averages are calculated from the cross-sectional estimates of these firm characteristics. The t-statistics are adjusted by the Newey-West (1987) method. We find that the RG is significantly and positively associated with future returns, indicating that higher returns follow higher RG, and vice versa. Model 1 of Table 3 strongly supports the hypothesis that RG has predictability on future stock returns. Even after controlling for important characteristics that determine stock returns, the results are still robust. Model 2 shows that the coefficient on RG is statistically significant at 0.003 (t-statistics = 4.62).

[Table 3 here]

3.3. Newly announced revenue information and PRAD

By the 10th day of each calendar month t, every publicly traded firm is required to file its operating revenue of the month t-1. Portfolio ranks at the end of month t are based on RG in month t-1, while portfolio returns are calculated in month t+1. During the holding month t+1, the operating revenue of month t is filed by the 10th day of month t+1. Therefore, it is possible that the newly announced revenue may affect the returns of the portfolio. Figure 2 demonstrates the lead-lag relation across portfolio formation, holding, and operating revenue announcement dates.

[Figure 2 here]

Since the newly announced revenue information is crucial, we use the persistent rank metric to be the proxy. We examine the extent to which stocks with the highest (lowest) RG in month t also have the highest (lowest) RG in the subsequent month. We try to analyze the percentage of stocks staying in the same rank during two consecutive months. Table 4 shows that 56.93% (56.50%) of stocks in the top (bottom) RG portfolio continue to experience the same rank next month. Compared to a randomly distributed percentage of 20%, our results indicate that the RG portfolio exhibits high RG rank persistence. The evidence is consistent with Jegadeesh and Livnat (2006) that revenues tend to be persistent.

[Table 4 here]

Next, we extend the holding periods of RG portfolio of Table 2 up to 36 months to examine whether the RG information has a long-lasting predictability on future RG.

From January 1990 to December 2020, at the end of each month t, we use lagged RG (month t-1) to sort all stocks into five groups, portfolio highest (H) contains stocks in Group 5, and the portfolio lowest (L) includes stocks in Group 1. The zero-cost portfolio (PRAD) is constructed as long-buying the highest RG stocks and short-selling the lowest RG stocks. The portfolios are held for 1 to 36 months and rebalanced each month. The overlapping portfolio returns are equally weighted. Figure 3 shows that PRAD exhibits a reversal pattern for the extended post-formation periods. The portfolio returns quickly dissipate. With increasing holding months, the predictive power of old RG information on future RG information is decaying. Thus, the PRAD is deteriorating with decreasing new RG information in the portfolio.

[Figure 3 here]

3.4. Predictive ability of past persistency

Our earlier results suggest that future persistence in portfolio ranks, i.e., newly announced revenue information, is essential for PRAD. However, is there a way to predict future persistence in RG ranks? We test whether previous RG rank persistence can predict future RG rank persistence. We conduct a portfolio analysis by independently double sorting all stocks into five by five, i.e., 25 groups, based on lagged one period and lagged two-period RG. Specifically, at the end of month t, we sort all stocks into five portfolio ranks based on RG in month t-1 (denoted as lagged one-period RG portfolio). At the end of month t-1, we sort all stocks into five portfolio ranks based on RG in month t-2 (denoted as lagged two-period RG portfolio). The prior persistent and non-persistent portfolios are constructed from the intersections of the five lagged one-period RG portfolios and five lagged two-period RG portfolios. The persistent group contains stocks with the same lagged one period and lagged two-period portfolio ranks, while the non-persistent group contains stocks with different RG portfolio ranks.

In Table 5, we show that PRAD mainly comes from prior persistence in RG ranks. When we separate stocks into persistent and non-persistent sub-groups, the non-persistent PRAD experiences insignificant returns, while persistent PRAD exhibits positive and significant returns of 1.582% and 1.053% for equally-weighted and value-weighted raw returns, respectively. Further, the persistent PRAD significantly outperforms the non-persistent PRAD. The equally-weighted (value-weighted) raw spread between the persistent PRAD and non-persistent PRAD is 1.227% (1.123%) per month with t-statistics of 2.45 (1.90). The Fama-French three-factor alphas on the difference between persistent and non-persistent PRAD are significantly positive. These results suggest that the prior persistence in RG ranks can predict future persistence in RG ranks, i.e., newly announced revenue information, which leads to positive PRAD.

[Table 5 here]

3.5. Explanations of underreaction to persistency in RG

Many studies suggest that mispricing is due to limited attention or other psychological biases (Bernard and Thomas (1989, 1990), Barber and Odean (2008), Barberis et al. (1998), Daniel et al. (1998), Hirshleifer et al. (2011), Hou et al. (2009), Li and Yu (2012)). Further, the anomalies might be due to arbitrage costs (Chordia et al. (2009), Ng et al. (2008), Mendenhall (2004)). In this section, we use two categories of variables to test what factors can explain the potential investor underreaction to possibilities of future persistency in RG.

The first category of variables is associated with attention bias, while the other is related to arbitrage costs. The attention bias variables include the 52-week high (George and Hwang (2004)), recency ratio (Bhootra and Hur (2013)), and information discreteness (Da et al. (2014)).[10] The arbitrage cost variables are market capitalization, illiquidity, relative bid-ask spread, and idiosyncratic volatility. The detailed definitions of the three attention measures are shown in Appendix A. From January 1990 to December 2020, for each month t, we form two-dimensional sequentially-sorted portfolios. First, we separate stocks into three groups by each stock control variable. Second, within each controlling group, we independently sort stocks into five portfolio ranks based on RG in month t-1 (lagged one period) and five portfolio ranks based on RG in month t-2 (lagged two periods). Within each controlling group, the prior persistent and non-persistent portfolios are constructed from the intersections of the five lagged one-period RG portfolios and five lagged two-period RG portfolios. The persistent groups contain stocks with the same lagged one and lagged two-period portfolio rank. We test whether attention or arbitrage cost-related variables affect how investors react to RG. The value-weighted raw return and Fama-French alpha are reported.[11]

First, Panel A of Table 6 shows that all persistent PRADs experience significant positive returns for four arbitrage-related control variables. Second, and more importantly, although the sign of the difference in persistent PRAD (Spread) is consistent with the argument of the arbitrage-cost hypothesis, the underreaction to RG persistency is statistically indifferent across arbitrage-cost variables. Specifically, the persistent PRAD is indistinguishable between high and low arbitrage cost variables. For example, the difference in persistent risk-adjusted PRAD between stocks with high and low market capitalization is -0.538%, with a t-statistic of -1.20. PRAD differences for the other three arbitrage-cost variables are also insignificantly different from zero.

[10]Following Hung et al. (2022), we use these three variables to proxy for attention bias.

[11] For brevity, we only provide value-weighted results. The equal-weighted results are quantitively similar and are available upon request.

George and Hwang (2004) show that investors use a 52-week high price as an essential reference point in their decision-making process. Investors are reluctant to bid up the price of stocks that are trading near their 52-week high, even if positive information warrants a higher valuation. George et al. (2015) examine whether anchoring on the 52-week high explains why markets underreact to extreme earnings news for individual stocks. They show that the anchoring on the 52-week high, not the surprise in earnings itself, drives the market's underreaction to extreme earnings news. In a similar vein, Goh and Jeon (2017) document that the PEAD effect is particularly pronounced when stocks are trading near their 52-week highs, possibly due to the influence of anchoring bias. Byun et al. (2020) also find that the overpriced lottery anomaly is present mainly among stocks that are far from their 52-week high prices. In other words, the mispricing is associated with how far the stocks are near their 52-week highs.

Panel B of Table 6 shows that the persistent PRAD is statistically stronger for stocks with a high 52-week high ratio than stocks with a low 52-week high ratio. For instance, the difference in persistent risk-adjusted PRAD between stocks with high and low 52-week high ratio (H52) is 1.037%, with a t-statistic of 1.86. The results indicate that, consistent with previous studies, investors underestimate the possibilities of future persistency for a stock with a high 52-week high ratio. Specifically, underreaction to future persistency occurs when stock prices are anchored near their 52-week high. Other investor attention variables, namely, the information discreteness and recency ratio, do not seem to affect investors' underreaction to future persistency in RG.

[Table 6 here]

4. Robustness checks

4.1. PRAD conditional on stock characteristics

To further verify the existence of the RG effect, we form two-dimensional sequentially-sorted portfolios based on stock characteristics and RG. First, we classify stocks into three groups by a given measure of stock characteristic. Second, we divide stocks into high and low RG within each group. The portfolios are held for one month. In addition to raw returns, the returns are adjusted for Fama-French three factors. We present the average zero-cost RG portfolio returns across the three (from low to high) groups for each characteristic. The detailed definitions of firm characteristics are shown in Appendix A.

In the real world, arbitrage is costly and risky. As a result, the mispricing of stocks might exist longer when the limits to arbitrage are more severe. We use the following stock characteristics to proxy for limits-to-arbitrage: market capitalization, Amihud (2002) illiquidity, relative bid-ask spread, and idiosyncratic volatility. Table 7 presents the average zero-cost RG portfolio returns across the three control groups. For each control characteristic, the raw and abnormal returns on the zero-cost RG portfolio are all significantly positive at the 1% level. Further, the evidence suggests that the RG portfolio returns cannot be explained by limits-to-arbitrage variables, such as market capitalization, Amihud (2002) illiquidity, relative bid-ask spread, and idiosyncratic volatility. In addition to our proxies for limits-to-arbitrage, we also include beta, price-to-book, one-month prior returns, and twelve-month prior returns in our analyses for robustness test. Overall, we find similar results across different firm characteristics, indicating that our results are robust to those important variables that are known to determine stock returns.

[Table 7 here]

4.2. Subperiod tests

Similar to the previous section, we apply Fama-MacBeth cross-sectional regressions to perform some subperiod tests for robustness in this section. First, we exclude the January coefficients since prior studies show that excluding January makes the effects of beta, size, and the bid-ask spread insignificant (e.g., Keim (1983), Tinic and West (1986), Eleswarapu and Reinganum (1993)). In Table 8, we report the average coefficients with and without January. The coefficient on RG remains positive and highly significant whether January is excluded or not, suggesting that our results are robust.

Further, we separate the time-series sample into pre-IFRS (International Financial Reporting Standards) and post-IFRS periods and compare PRAD between these two periods to test whether the adoption of IFRS allows investors to react more completely to revenue news. On one hand, Hung et al. (2015) treat the adoption of IFRS as an exogenous information shock and document that the increased financial reporting quality reduces uncertainty. On the other hand, Ahmed et al. (2013) show that accounting quality declined after the mandatory IFRS adoption. Taiwan Stock Exchange adopted the IFRS in 2013. If IFRS improves accounting quality, we should see lower PRAD during the post-IFRS period than the pre-IFRS period. The results in Table 8 show that the RG effect is positive and significant in both sub-periods, indicating that the RG effect is not significantly affected by the IFRS adoption.

We also examine whether the RG effect is stronger during optimistic periods than pessimistic periods. We use three classifications, namely, market return, business cycle indicator, and investor sentiment, to split the sample into optimistic and pessimistic periods. The market return is based on the Taiwan Stock Exchange Index. The monthly business cycle indicators are provided by the Taiwan National Development Council. We use the consumer confidence index obtained from the National Central University to proxy for investor sentiment (Antoniou et al. 2013).[12] The up (down) market months occur when monthly market returns are positive (negative). We define month t as expansion (recession) if the value of the business cycle indicator in month t is greater (lower) than 23 points, the median values of the business cycle indicator from January 1990 to December 2020. The month t is defined as high (low) sentiment if the consumer confidence score is higher than 77 points, the median value of the consumer confidence index from January 2001 to December 2020. The results of Table 8 show that the coefficients on RG are all significantly positive for all subperiods, suggesting that the predictability of RG is not specific to a certain period.

[Table 8 here]

4.3. Quarterly earnings and monthly revenues

Previous studies mostly analyze quarterly financial reports given their availability. However, because quarterly financial reports aggregate three months' information, any exogenous shocks taking place in the quarter cannot be precisely detected through the quarterly financial statements. Furthermore, the time between the end of the calendar quarter and the date of filing the report is too long to determine whether the market is surprised or affected by other news. DeFond et al. (2007) find that the market reaction to less frequent financial reporting, such as annual earnings, is weaker when more frequent interim financial reporting is announced, indicating that earnings information has already impounded into the price. Taiwan is the only country that requires firms to disclose operating revenues for the preceding month by the 10th day of each calendar month. Using such unique interim data, i.e., monthly revenues, can partially mitigate the problem of potential shocks that could affect stock returns whithin a quarter and

[12]Data of business cycle indicators are assessed from the http://index.ndc.gov.tw/n/en. The data of investor sentiment is from http://rcted.ncu.edu.tw.

help examine whether the market incorporates the interim information into the stock price. Specifically, we test if earnings information is already impounded into the price when the high-frequency data, i.e., monthly revenue growth, is announced. If this is the case, we expect the PRAD and PEAD to be highly correlated.

From January 1990 to December 2020, for each month t, we form two-dimensional sequentially-sorted portfolios based on stock's RG and then SUE. First, we separate stocks into three groups by each stock's RG. Second, we further divide stocks into ten SUE groups within each RG group. Panel A of Table 9 shows that either for stocks with low RG or high RG, the PEAD portfolio (high minus low SUE portfolio) exhibits significantly positive raw and risk-adjusted returns. In other words, the lower frequency PEAD is not affected by the higher frequency PRAD, which is inconsistent with DeFond et al. (2007).

On the other hand, we also do the reverse two-dimensional sequentially-sorted portfolios based first on stock's SUE and then RG. Panel B of Table 9 indicates that the PRAD is significantly positive for low or high SUE stocks. Thus, the PRAD is also not affected by the SUE. The evidence indicates that the information on quarterly earnings announcements and monthly revenue growth is different.

[Table 9 here]

5. Conclusions

Adopting a unique dataset of monthly operating revenues in Taiwan, we contribute to the behavioral literature by documenting significantly positive PRAD, i.e., stocks with high RG earn higher future returns than stocks with low RG. The positive relation between RG and future stock returns indicates that stocks with the highest RG tend to be underpriced, and stocks with the lowest RG tend to be overpriced. The PRAD is robust to arbitrage-cost variables. Further, the PRAD is not driven by well-known variables, such as price-to-book ratio, beta, turnover ratio, one-month prior returns, and twelve-month prior returns, that predict cross-sectional stock returns. More significantly, the PRAD is not driven by quarterly earnings announcement drifts. The results are also robust to subperiods separated by January, the adoption of IFRS, investor sentiment, market return, and business cycle indicator. The evidence suggests that the RG might be another important characteristic in explaining stock returns in the Taiwan stock market.

Our findings provide ample evidence to suggest that the positive PRAD is largely driven by the persistence in RG ranks. First, stocks with high RG are likely to have high RG in the following month. Second, PRAD exhibits a reversal pattern during the extended post-formation periods. The overlapping PRAD returns quickly dissipate in the short term. With increasing holding months, the predictive power of old RG information on future RG information is decaying. With decreasing new RG information in the portfolio, the PRAD is deteriorating. Finally, the prior persistency can significantly enhance PRAD.

We also show that investors tend to underreact to the possibility of RG persistency due to anchoring bias. The evidence suggests that the underreaction to the possibilities of future persistency is significantly stronger for stocks with a high 52-week ratio than those with a low 52-week ratio, indicating that investors are reluctant to bid up the price of stocks that are trading near 52-week high when the stocks have a high likelihood of persistence in RG.

Appendix A. Variables definitions

1. Revenue growth (RG)
   The revenue growth (RG) is defined as the monthly growth rate of operating revenue to the operating revenue with the same calendar month of the previous year. We winsorize RG at top-bottom 1% in distribution.
2. Size (MV, millions)
   MV is defined as the market value of equity at the month-end prior to the portfolio formation.
3. Price-to-book equity (PB)
   PB is denoted as the stock price scaled by the book value of equity per share as reported at the end of the most recent fiscal year.
4. Idiosyncratic volatility (IVOL)
   We measure idiosyncratic volatility each month as the standard deviation of the residual returns from the Fama–French three-factor model by regressing the daily returns of individual stocks in excess of the one-month Bank of Taiwan deposit rate on the daily returns to the common factors related to market, size, and book-to-market ratio. We require a minimum of 15 observations for model estimation.
5. Systematic risk (BETA)
   For each firm and month, we estimate systematic risk by regressing daily excess returns on market risk premium.
6. Prior returns (PR01)
   PR01 is defined as one-month return of firm at the month-end prior to the portfolio formation.
7. Prior returns (PR12)
   PR12 is defined as twelve-month return (skip the most recent month) of firm at the month-end prior to the portfolio formation.
8. Turnover (TURN)
   TURN is the ratio of monthly trading volume to shares outstanding at the month-end prior to the portfolio formation.
9. Amihud illiquidity (ILQD)
   According to Amihud (2002), illiquidity measure is the average ratio of the daily absolute return to the dollar trading volume on that day. The measure is multiplied by 10^6.
10. Relative bid-ask spread (BASK)
    BASK is the average ratio of daily bid-ask spread to the daily bid-ask midpoint in the month.
11. 52-week high price ratio (H52)
    H52 is defined as the ratio of current price to the previous 12-month (skip the most recent month) maximum price.
12. Recency ratio (RR)
    RR is defined as 1 - (number of days since 52-week high price)/364.
13. Information discreteness (ID)
    ID is defined as ID = sgn(PRET) × [%neg −%pos], where PRET is the cumulative return during the formation period. sgn(PRET) is denoted as the sign of PRET. sgn(PRET) = 1 if PRET > 0 and sgn(PRET) = -1 if PRET < 0. %neg and %pos are the percentage of days during the formation period with positive and negative returns.
14. Standardized unexpected earnings (SUE)
    SUE is defined as SUE = $(QEPS_t - QEPS_{t-4})/\sigma_t$, where $QEPS_t$ is the most recently announced quarterly earnings per share and σ_t is the standard deviation of $(QEPS_t - QEPS_{t-4})$ over the prior eight quarters.

References

1. Ahmed, A. S., Neel, M., & Wang, D. (2013). Does mandatory adoption of IFRS improve accounting quality? Preliminary evidence. Contemporary accounting research, 30(4), 1344-1372.
2. Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. Journal of Financial and Quantitative Analysis, 48(1), 245-275.
3. Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets, 5(1), 31-56.
4. Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. Journal of accounting research, 159-178.
5. Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The review of financial studies, 21(2), 785-818.
6. Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of financial economics, 49(3), 307-343.
7. Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: delayed price response or risk premium? Journal of Accounting Research, 27, 1-36.
8. Bhootra, A., & Hur, J. (2013). The timing of 52-week high price and momentum. Journal of Banking & Finance, 37(10), 3773-3782.
9. Brav, A., Heaton, J. B., & Li, S. (2010). The limits of the limits of arbitrage. Review of Finance, 14(1), 157-187.
10. Byun, S. J., Goh, J., & Kim, D. H. (2020). The role of psychological barriers in lottery-related anomalies. Journal of Banking & Finance, 114, 105786.
11. Chan, L. K., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. The Journal of Finance, 51(5), 1681-1713.
12. Chen, H. Y., Chen, S. S., Hsin, C. W., & Lee, C. F. (2014). Does revenue momentum drive or ride earnings or price momentum?. Journal of Banking & Finance, 38, 166-185.
13. Chordia, T., Goyal, A., Sadka, G., Sadka, R., & Shivakumar, L. (2009). Liquidity and the post-earnings-announcement drift. Financial Analysts Journal, 65(4), 18-32.
14. Da, Z., Gurun, U. G., & Warachka, M. (2014). Frog in the pan: Continuous information and momentum. The review of financial studies, 27(7), 2171-2218.
15. Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. the Journal of Finance, 53(6), 1839-1885.
16. DeFond, M., Hung, M., & Trezevant, R. (2007). Investor protection and the information content of annual earnings announcements: International evidence. Journal of Accounting and Economics, 43(1), 37-67.
17. Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. Journal of financial economics, 49(3), 283-306.
18. Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of financial economics, 33(1), 3-56.
19. George, T. J., & Hwang, C. Y. (2004). The 52-week high and momentum investing. The Journal of Finance, 59(5), 2145-2176.
20. George, T. J., Hwang, C. Y., & Li, Y. (2015). Anchoring, the 52-week high and post earnings announcement drift. Available at SSRN 2391455.

21. Goh, J., & Jeon, B. H. (2017). Post-earnings-announcement-drift and 52-week high: Evidence from Korea. Pacific-Basin Finance Journal, 44, 150-159.
22. Hao, Y., Chu, H. H., Ho, K. Y., & Ko, K. C. (2016). The 52-week high and momentum in the Taiwan stock market: Anchoring or recency biases?. International Review of Economics & Finance, 43, 121-138.
23. Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2011). Limited investor attention and stock market misreactions to accounting information. The Review of Asset Pricing Studies, 1(1), 35-73.
24. Hou, K., Xiong, W., & Peng, L. (2009). A tale of two anomalies: The implications of investor attention for price and earnings momentum. Available at SSRN 976394.
25. Hung, M., Li, X., & Wang, S. (2015). Post-earnings-announcement drift in global markets: Evidence from an information shock. The Review of Financial Studies, 28(4), 1242-1283.
26. Hung, W., Lin, C. T., & Yang, J. J. (2022). Aggregate 52-week high, limited attention, and time-varying momentum profits. Journal of Banking & Finance, 106531.
27. Jegadeesh, N., & Livnat, J. (2006). Revenue surprises and stock returns. Journal of Accounting and Economics, 41(1-2), 147-171.
28. Li, J., & Yu, J. (2012). Investor attention, psychological anchors, and stock return predictability. Journal of Financial Economics, 104(2), 401-419.
29. Mendenhall, R. R. (2004). Arbitrage risk and post-earnings-announcement drift. The Journal of Business, 77(4), 875-894.
30. Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703-708.
31. Ng, J., Rusticus, T. O., & Verdi, R. S. (2008). Implications of transaction costs for the post–earnings announcement drift. Journal of Accounting Research, 46(3), 661-696.
32. Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and uncertainty, 5(4), 297-323.
33. Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings?. Accounting review, 289-315.

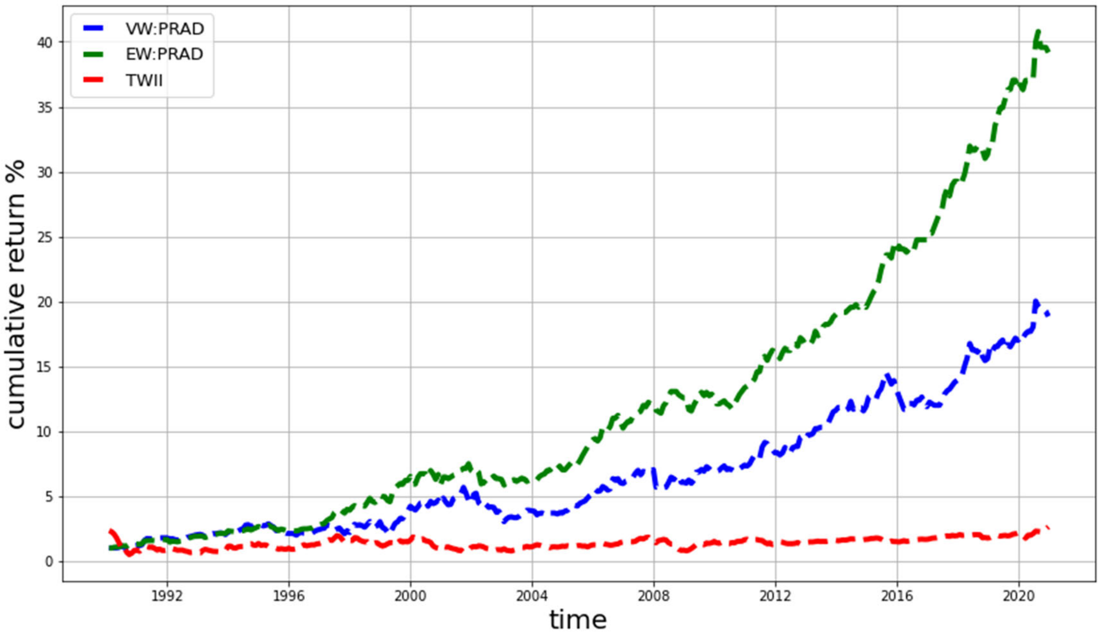

Figure 1. Cumulative returns of PRADs

The figure plots cumulative returns on equally-weighted (EW: PRAD), value-weighted (VW: PRAD) PRADs, and market return of the Taiwan Stock Exchange (TWII).

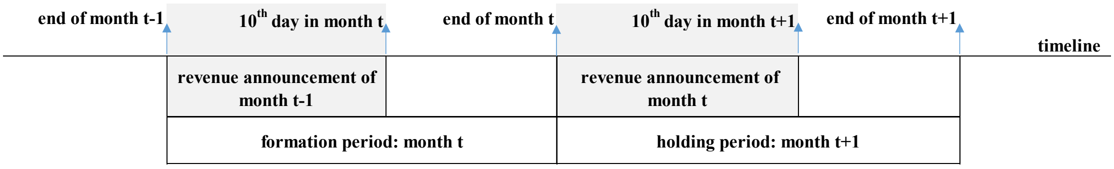

Figure 2. Timeline of forming portfolio and announcements of monthly revenue

The figure demonstrates the lead-lag relation across portfolio formation, holding, and operating revenue announcement dates.

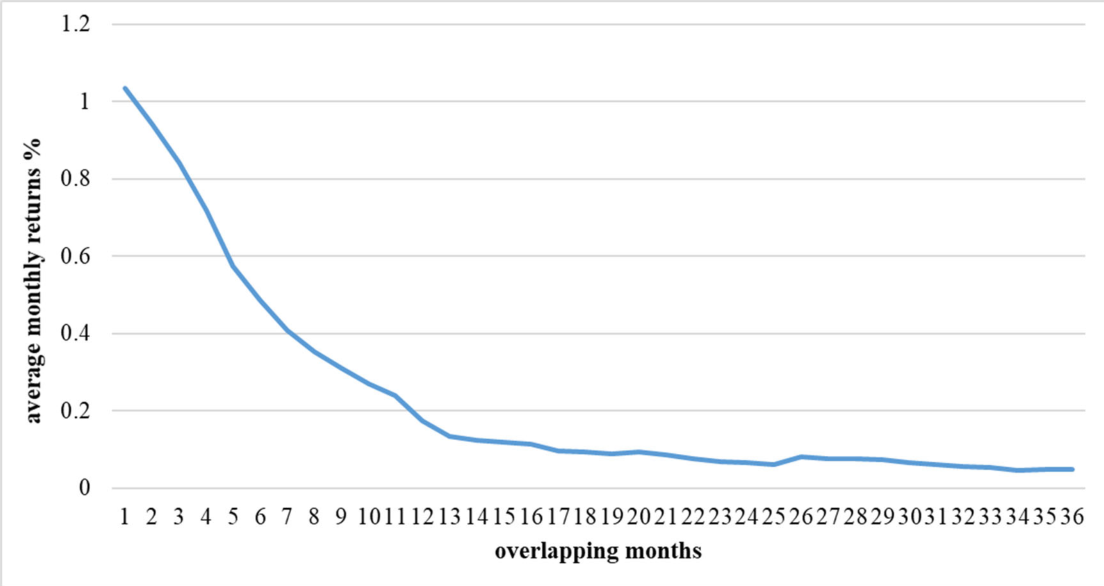

Figure 3. Overlapping returns of PRAD in each month following the formation period

From January 1990 to December 2020, at the end of each month t, we use RG in month t-1 (RG) to sort all stocks into five groups, portfolio highest contains stocks in Group 5, and the portfolio lowest includes the stocks in Group 1. The PRAD is constructed as long-buying the highest RG stocks and short-selling the lowest RG stocks. The portfolios are held for 1 to 36 months and rebalanced for each month.

Table 1. Descriptive statistics and correlations among firm characteristics.

Panel A presents the summary statistics for firm characteristics. The definitions of firm characteristics are in Appendix A. Panel B presents the Pearson correlation among variables. From January 1990 to December 2020, month-stock observations are 199,897.

Panel A: Summary statistics

	Mean	Std.	10^{th} pct.	Median	90^{th} pct.
RG (%)	12.63	64.22	-32.43	2.84	52.42
MV (NTD millions)	20352	64229	1154	5246	36523
PB	1.86	3.27	0.64	1.36	3.41
TURN (%)	16.41	24.45	1.24	7.65	41.54
BETA	0.77	0.96	0.03	0.74	1.56
IVOL (%)	1.58	0.92	0.63	1.41	2.73
ILQD	1.20	4.92	0.01	0.12	1.81
BASK (%)	0.46	0.48	0.15	0.36	0.81
PR01 (%)	1.04	13.26	-12.36	0.00	14.80
PR12 (%)	12.27	55.42	-36.38	2.56	66.71

Panel B: Pearson correlations

	RG	MV	PB	PR01	TURN	ILQD	BASK	IVOL	BETA	PR12
RG	1.00	0.02	0.07	0.04	0.08	0.00	0.00	0.05	0.02	0.19
MV		1.00	0.08	0.01	-0.06	-0.07	-0.11	-0.09	0.05	0.04
PB			1.00	0.07	0.13	0.02	-0.02	0.09	0.02	0.17
PR01				1.00	0.25	-0.03	-0.05	0.27	-0.05	0.00
TURN					1.00	-0.13	-0.21	0.41	0.14	0.28
ILQD						1.00	0.50	0.13	-0.08	-0.07
BASK							1.00	0.16	-0.10	-0.06
IVOL								1.00	0.11	0.14
BETA									1.00	0.07
PR12										1.00

Table 2. Post-revenues-announcement drift

The table reports the average returns (raw) and Fama and French three-factor adjusted returns (alpha). From January 1990 to December 2020, at the end of each month t, we use revenue growth in month t-1 (RG) to sort all stocks into five groups, portfolio High contains stocks with the highest RG, and portfolio Low includes the stocks with the lowest RG. The post-revenues-announcement drift (PRAD) is the difference in average returns between the highest and lowest RG stocks. The portfolios are held for one month and rebalanced for each month, and the portfolio returns are either equally (EW) or value-weighted (VW). Panel B reports the average firm characteristics. The detailed definitions of the variables are shown in Appendix A. The t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Returns (%)

	Low	2	3	4	High	PRAD
EW raw	0.481	0.600	0.929**	1.041**	1.515***	1.035***
	(0.97)	(1.32)	(2.11)	(2.39)	(3.16)	(6.00)
EW FF alpha	-0.162	0.000	0.344***	0.468***	0.923***	1.085***
	(-1.35)	(0.00)	(3.45)	(4.93)	(7.01)	(6.69)
VW raw	0.042	0.190	0.672*	0.620	0.964**	0.922***
	(0.09)	(0.48)	(1.73)	(1.58)	(2.09)	(3.52)
VW FF alpha	-0.422**	-0.216	0.294**	0.231*	0.578***	1.000***
	(-2.47)	(-1.51)	(2.35)	(1.79)	(3.28)	(3.99)
Panel B: Characteristics						
RG (%)	-37.18	-9.08	3.16	17.03	88.91	126.09
MV (millions)	14,032	19,487	22,944	24,142	22,805	8,774
PB	1.57	1.59	1.73	1.90	2.23	0.66
TURN (%)	14.22	13.90	14.33	17.03	22.51	8.29
BETA	0.74	0.75	0.75	0.78	0.83	0.09
IVOL (%)	1.64	1.47	1.44	1.51	1.72	0.08
ILQD	1.68	1.16	1.02	0.89	1.11	-0.57
BASK (%)	0.55	0.47	0.44	0.42	0.45	-0.10
PR01 (%)	-0.15	0.32	0.77	1.59	2.75	2.90
PR12 (%)	0.76	3.71	9.35	15.66	27.97	27.21

Table 3. Cross-sectional regressions of stock returns

This table reports the estimated coefficients of the Fama-MacBeth regressions of the monthly return of all firms on the RG and controlling variables. For each month from January 1990 to December 2020, we cross-sectionally regress returns on independent variables by OLS. The time-series averages are calculated from the cross-sectional estimates of these firm characteristics. Average parameter values are the time-series averages, and *t*-statistics are the time-series averages divided by the time-series standard errors. Newey-West (1987) *t*-statistics with 12 lags are shown in parentheses. The asterisks *, **, and *** indicate significance at the 10, 5, and 1 levels, respectively.

	Model 1	Model 2
Intercept	1.009**	0.964**
	(2.56)	(2.55)
RG	0.003***	0.003***
	(3.53)	(4.62)
MV		-0.000
		(-1.24)
PB		-0.051
		(-0.76)
TURN		-0.014***
		(-3.51)
ILQD		0.094***
		(3.35)
BASK		24.383
		(1.61)
IVOL		-0.207***
		(-2.63)
BETA		0.106
		(0.83)
PR01		0.011**
		(1.99)
PR12		0.743***
		(3.66)

Table 4. Transition matrix for RG portfolios (in percentage)

From January 1990 to December 2020, at the end of each month t, all stocks are sorted into ascending five RG portfolios. For each month t RG portfolio, the table presents the time-series averages of the percentage of stocks in the given month t RG portfolio that fall in each month t + 1 RG portfolio.

		time t +1				
		Low	2	3	4	High
time t	Low	**56.50**	19.82	9.06	6.25	8.37
	2	20.10	**37.62**	23.64	12.60	6.04
	3	8.96	24.07	**34.28**	23.88	8.81
	4	6.02	12.63	24.36	**37.32**	19.68
	High	8.10	6.08	8.77	20.13	**56.93**

Table 5. Prior persistence and PRAD

The table reports the average returns (raw) and Fama and French three-factor adjusted returns (alpha). From January 1990 to December 2020, at the end of each month t, we sort all stocks into five portfolio ranks based on RG in month t-1 (lagged one period), and at the end of month t-1, we sort all stocks into five portfolio ranks based on RG in month t-2 (lagged two periods). The prior persistent and non-persistent portfolios are constructed from the intersections of the five lagged one-period RG portfolios and five lagged two-period RG portfolios. The persistent groups contain stocks with the same lagged one and lagged two-period portfolio rank. The non-persistent groups contain stocks with different RG portfolio ranks during month t-1 and month t-2. For instance, the portfolio "Low_{per}" contains stocks with the lowest portfolio rank during month t and month t-1. The persistent PRAD ($PRAD_{per}$) is constructed as long buying persistent highest RG stocks and short selling persistent lowest RG stocks. The non-persistent PRAD ($PRAD_{no}$) is constructed as long buying non-persistent highest RG stocks and short selling non-persistent lowest RG stocks. The spread is defined as the difference between $PRAD_{per}$ and $PRAD_{no}$. The portfolios are held for one month in month t+1 and rebalanced for each month, and the portfolio returns are either equally (EW) or value-weighted (VW). The t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Low_{per}	$High_{per}$	$PRAD_{per}$	Low_{no}	$High_{no}$	$PRAD_{no}$	**Spread**
EW Raw	0.304	1.886***	1.582***	0.608	0.963	0.355	1.227**
	(0.57)	(3.68)	(6.28)	(1.09)	(1.61)	(0.85)	(2.45)
EW FF alpha	-0.233	1.469***	1.702***	0.364	0.368	0.004	1.698***
	(-1.44)	(7.19)	(7.67)	(1.17)	(1.22)	(0.01)	(3.74)
VW Raw	-0.038	1.015**	1.053***	0.433	0.364	-0.070	1.123*
	(-0.07)	(1.97)	(3.12)	(0.75)	(0.61)	(-0.15)	(1.90)
VW FF alpha	-0.428*	0.725***	1.153***	0.227	-0.248	-0.475	1.627***
	(-1.95)	(3.35)	(3.67)	(0.61)	(-0.81)	(-1.08)	(2.96)

Table 6. Arbitrage cost, investor attention, and persistent PRAD

For each month t from January 1990 to December 2020, first, we separate stocks into three groups by each of the stock control variables, including arbitrage cost-related and investor attention-related. Second, within each controlling group, we independently sort stocks into five portfolio ranks based on RG in month t-1 (lagged one period) and five portfolio ranks based on RG in month t-2 (lagged two periods). Within each controlling group, the prior persistent and non-persistent portfolios are constructed from the intersections of the five lagged one-period RG portfolios and five lagged two-period RG portfolios. The persistent groups contain stocks with the same lagged one and lagged two-period portfolio rank. For instance, the portfolio "Low$_{per}$" contains stocks with the lowest portfolio rank during month t and month t-1. The PRAD is constructed as long buying persistent highest RG stocks (High$_{per}$) and short selling persistent lowest RG stocks (Low$_{per}$). The Spread is the difference (High minus Low) between PRADs in two extreme control portfolios. The portfolios are held for one month in month t+1 and rebalanced for each month, and the portfolio returns are either equally (EW) or value-weighted (VW). The arbitrage cost measures include market value (MV), Amihud illiquidity (ILQD), Relative bid-ask spread (BASK), and idiosyncratic volatility (IVOL). The attention measures include the nearness to the 52-week high (H52), the information discreteness (ID), and the recency ratio (RR). The t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Variables associated with arbitrage cost

	Low MV			High MV				Low ILQD			High ILQD			
	Low$_{per}$	High$_{per}$	PRAD	Low$_{per}$	High$_{per}$	PRAD	**Spread**	Low$_{per}$	High$_{per}$	PRAD	Low$_{per}$	High$_{per}$	PRAD	**Spread**
VW Raw	0.651	2.202***	1.550***	0.146	1.188**	1.041***	-0.509	-0.087	0.829	0.916**	0.449	1.957***	1.508***	0.592
	(0.99)	(4.03)	(4.24)	(0.30)	(2.41)	(3.02)	(-1.12)	(-0.16)	(1.59)	(2.42)	(0.93)	(4.10)	(4.10)	(1.21)
VW alpha	-0.116	1.555***	1.672***	-0.272	0.861***	1.134***	-0.538	-0.571**	0.415	0.986***	-0.116	1.474***	1.589***	0.603
	(-0.43)	(6.72)	(4.79)	(-1.20)	(3.42)	(3.42)	(-1.20)	(-2.07)	(1.55)	(2.64)	(-0.51)	(5.21)	(4.39)	(1.24)

	Low BASK			High BASK				Low IVOL			High IVOL			
	Low$_{per}$	High$_{per}$	PRAD	Low$_{per}$	High$_{per}$	PRAD	**Spread**	Low$_{per}$	High$_{per}$	PRAD	Low$_{per}$	High$_{per}$	PRAD	**Spread**
VW Raw	0.127	1.131**	1.005**	0.488	1.537***	1.049**	0.044	-0.052	0.867*	0.919***	0.180	1.596***	1.416***	0.497
	(0.24)	(2.20)	(2.46)	(1.00)	(2.97)	(2.33)	(0.09)	(-0.12)	(1.86)	(2.78)	(0.27)	(2.72)	(2.92)	(0.95)
VW alpha	-0.459	0.643**	1.102***	-0.143	1.017***	1.161***	0.059	-0.504**	0.471**	0.975***	-0.412	1.155***	1.567***	0.592
	(-1.62)	(2.34)	(2.77)	(-0.56)	(3.30)	(2.75)	(0.12)	(-2.08)	(1.97)	(3.08)	(-1.14)	(3.21)	(3.35)	(1.16)

Panel B: Variables associated with investor attention

	Low ID			High ID				Low RR			High RR			
	Low_{per}	$High_{per}$	PRAD	Low_{per}	$High_{per}$	PRAD	**Spread**	Low_{per}	$High_{per}$	PRAD	Low_{per}	$High_{per}$	PRAD	**Spread**
VW Raw	0.266	1.610***	1.344***	-0.145	0.719	0.989***	-0.363	-0.668	0.293	0.986***	0.520	1.671***	1.151***	0.133
	(0.47)	(2.86)	(2.91)	(-0.28)	(1.45)	(2.77)	(-0.65)	(-1.31)	(0.62)	(2.89)	(0.97)	(3.00)	(2.64)	(0.26)
VW alpha	-0.273	1.198***	1.472***	-0.594**	0.298	0.998***	-0.498	-1.205***	-0.153	1.067***	0.050	1.334***	1.283***	0.183
	(-0.89)	(3.74)	(3.28)	(-2.12)	(1.23)	(2.87)	(-0.93)	(-4.52)	(-0.58)	(3.19)	(0.18)	(3.68)	(3.04)	(0.35)

	Low H52			High H52			
	Low_{per}	$High_{per}$	PRAD	Low_{per}	$High_{per}$	PRAD	**Spread**
VW Raw	0.145	0.766	0.621	0.123	1.768***	1.645***	1.024*
	(0.22)	(1.20)	(1.54)	(0.25)	(3.55)	(4.10)	(1.84)
VW alpha	-0.485	0.189	0.674*	-0.272	1.440***	1.711***	1.037*
	(-1.40)	(0.59)	(1.68)	(-0.99)	(4.98)	(4.35)	(1.86)

Table 7. PRAD controlling for stock characteristics

From January 1990 to December 2020, at the end of each month t, we form two-dimensional sequentially-sorted portfolios based on stock characteristics and RG. First, we separate stocks into three groups by a given measure of stock characteristics. Second, we further divide stocks into high and low RG groups within each characteristics group. The reported returns are the average high- and low-RG portfolio returns across the three control groups. Please see the detailed definitions of stock characteristics in Appendix A. The t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	MV	PB	TURN	BETA	IVOL	ILQD	BASK	PR01	PR12
EW Raw	1.357***	1.394***	1.226***	0.991***	0.988***	1.289***	1.122***	1.154***	0.816***
	(6.17)	(7.21)	(5.59)	(4.49)	(4.58)	(5.72)	(4.90)	(5.14)	(4.05)
EW FF alpha	1.293***	1.325***	1.222***	1.079***	1.082***	1.321***	1.218***	1.088***	0.843***
	(6.60)	(7.18)	(6.20)	(5.43)	(5.79)	(6.64)	(6.29)	(5.65)	(4.54)
VW Raw	1.374***	1.009***	1.249***	0.956***	1.048***	1.292***	1.182***	1.185***	0.891***
	(5.98)	(4.28)	(4.47)	(3.35)	(3.53)	(5.19)	(3.79)	(4.24)	(3.81)
VW FF alpha	1.282***	0.888***	1.281***	1.034***	1.142***	1.275***	1.299***	1.107***	0.905***
	(6.29)	(3.85)	(4.89)	(3.87)	(4.29)	(5.61)	(4.78)	(4.44)	(4.05)

Table 8. Subperiod tests

This table reports the estimated coefficients of the Fama-MacBeth regressions in different sub-periods from January 1990 to December 2020. The up (down) market months are defined as when market returns are positive (negative). We define month *t* as expansion (recession) if the value of the business cycle indicator in month t is greater (lower) than 23 points. Twenty-three points are the median values of the business cycle indicator from January 1990 to December 2020. The month t is defined as high (low) sentiment if the consumer confidence score is higher than 77 points. Seventy-seven points are the median values of the consumer confidence index from January 2001 to December 2020. The asterisks *, **, and *** indicate significance at the 10, 5, and 1 levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
	Pre-IFRS	Post-IFRS	Jan.	Non-Jan.	Up	Down	Expan.	Reces.	High sen.	Low sen.
Intercept	0.919*	1.088***	1.196*	0.843**	3.032***	-2.024***	1.359***	0.468	0.702*	1.560**
	(1.80)	(3.82)	(1.87)	(2.20)	(7.23)	(-5.11)	(3.45)	(1.06)	(1.71)	(2.27)
RG	0.003***	0.002***	0.002***	0.003***	0.003***	0.003**	0.002**	0.004***	0.003***	0.003**
	(4.16)	(3.38)	(3.02)	(4.18)	(4.44)	(2.60)	(2.32)	(4.68)	(4.18)	(2.48)
MV	-0.000	-0.000**	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000**
	(-0.67)	(-2.33)	(-0.21)	(-1.42)	(-0.89)	(-0.98)	(-0.93)	(-1.33)	(-0.83)	(-2.32)
PB	-0.074	-0.031	-0.253	-0.079	-0.068	-0.007	-0.148*	0.006	-0.062	-0.139
	(-0.81)	(-0.66)	(-0.93)	(-1.19)	(-0.67)	(-0.08)	(-1.78)	(0.08)	(-0.84)	(-1.06)
TURN	-0.018***	-0.009	0.008	-0.016***	-0.006	-0.028***	-0.017**	-0.013***	-0.023***	-0.015***
	(-3.58)	(-1.37)	(0.70)	(-3.62)	(-0.89)	(-5.06)	(-2.54)	(-2.66)	(-2.71)	(-2.78)
ILQD	0.126***	0.012	0.117	0.096***	0.041	0.153***	0.114**	0.059***	0.039*	0.036**
	(3.52)	(0.58)	(1.54)	(2.72)	(1.49)	(3.35)	(2.45)	(3.34)	(1.88)	(2.07)
BASK	20.688	20.303	-2.090	24.295	1.815	52.756**	33.221*	14.698	16.284	15.154
	(1.07)	(0.95)	(-0.06)	(1.48)	(0.07)	(2.01)	(1.73)	(0.77)	(0.98)	(0.57)
IVOL	-0.229**	-0.084	0.584	-0.257***	0.243*	-0.792***	-0.057	-0.377***	-0.247*	-0.127
	(-2.29)	(-0.78)	(1.07)	(-3.11)	(1.66)	(-7.42)	(-0.62)	(-3.34)	(-1.88)	(-1.06)
BETA	0.097	0.207**	0.086	0.094	0.841***	-0.835***	-0.060	0.271	0.074	0.095
	(0.56)	(2.25)	(0.23)	(0.68)	(4.69)	(-5.28)	(-0.38)	(1.62)	(0.70)	(0.34)
PR01	0.004	0.030***	-0.071**	0.017***	-0.003	0.029***	0.013	0.010	0.021**	0.009
	(0.63)	(2.94)	(-2.60)	(2.73)	(-0.38)	(3.44)	(1.44)	(1.05)	(2.59)	(0.93)
PR12	0.696**	0.689***	-0.936	0.830***	0.254	1.301***	1.206***	0.298	0.753***	0.423
	(2.50)	(4.26)	(-1.15)	(3.84)	(0.74)	(3.85)	(4.23)	(1.04)	(3.65)	(1.43)

Table 9. PRAD and PEAD

From January 1990 to December 2020, for each month *t*, we form two-dimensional sequentially-sorted portfolios first based on stock's RG (SUE) and then the SUE (RG). First, we separate stocks into three groups by each of the stock's RG (SUE). Second, within each RG (SUE) group, we further divide stocks into ten groups by SUE (RG). The spread is the difference between (PEADs) PRADs in two extreme control portfolios. The detailed definitions of SUE and RG are shown in Appendix A. The t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First RG, then SUE

	Low RG			High RG			
	Low SUE	High SUE	PEAD	Low SUE	High SUE	PEAD	**Spread**
EW Raw	-0.172	1.150**	1.321***	0.772	1.753***	0.982***	-0.340
	(-0.31)	(2.27)	(4.93)	(1.61)	(3.49)	(3.35)	(-0.97)
EW alpha	-0.855***	0.513**	1.368***	0.151	1.160***	1.009***	-0.359
	(-3.95)	(2.46)	(5.12)	(0.92)	(4.33)	(3.38)	(-1.01)
VW Raw	-0.278	0.493	0.771*	0.355	1.614***	1.259***	0.488
	(-0.50)	(0.95)	(1.80)	(0.72)	(2.96)	(2.81)	(0.96)
VW alpha	-0.906***	-0.116	0.790*	-0.226	1.056***	1.282***	0.492
	(-2.89)	(-0.41)	(1.83)	(-0.84)	(2.83)	(2.83)	(0.95)

Panel B: First SUE, then RG

	Low SUE			High SUE			
	Low RG	High RG	PRAD	Low RG	High RG	PRAD	**Spread**
EW Raw	-0.231	0.544	0.775***	1.151**	1.898***	0.748**	-0.027
	(-0.41)	(1.18)	(2.83)	(2.34)	(3.67)	(2.47)	(-0.08)
EW alpha	-0.920***	-0.047	0.873***	0.528***	1.294***	0.765***	-0.107
	(-3.96)	(-0.27)	(3.43)	(2.77)	(4.67)	(2.57)	(-0.30)
VW Raw	-0.387	0.165	0.552	0.635	1.508***	0.872**	0.320
	(-0.65)	(0.36)	(1.24)	(1.31)	(2.67)	(2.16)	(0.58)
VW alpha	-1.034***	-0.381	0.653	0.075	0.946**	0.871**	0.218
	(-2.89)	(-1.49)	(1.52)	(0.27)	(2.40)	(2.21)	(0.39)