Market Reaction to Monthly Revenue Momentum

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Abstract

Using mandated monthly revenue reports from the Taiwan Stock Exchange, we reveal positive revenue momentum using year-over-year revenue growth rates. The results of our analysis indicate that stock prices incorporate monthly revenue information independent of quarterly revenue announcements. Strong persistence in revenue growth considerably increases profits resulting from revenue momentum, particularly for stocks with high arbitrage costs. This persistence in revenue growth momentum is found to be robust in characteristics and subsample tests.

Keywords: monthly revenue, revenue growth, persistence, revenue momentum

1. Introduction

TSMC's Sales Gain 9.4% in First Two Months After AI Boost

Taiwan Semiconductor Manufacturing Co.'s revenue rose 9.4% in 2024's first two months, riding a wave of global AI development that's helping offset potential fallout from slowing iPhone sales. Asia's largest company reported sales of NT$397.4 billion ($12.6 billion) from January to February.[1]

-Bloomberg 2024/03/08

Earnings and corporate revenue considerably influence stock returns.[2] For example, Jegadeesh and Livnat (2006) document substantial abnormal returns in the post-announcement period for stocks that experience unexpected high revenue growth (RG). Additionally, Chen et al. (2014) indicate that unexpected revenues convey exclusive unpriced information.

Following Jegadeesh and Livnat (2006), we construct a strategy of revenue momentum for stocks based on year-over-year (YoY) RG, which is defined as the growth rate of operating revenue from the same calendar month of the previous year. The profit derived from revenue momentum is calculated as the difference in the average monthly returns between firms in the top and bottom RG quintiles. We use the YoY RG rate because it is the measurement most commonly disclosed in mainstream financial news.[3] The YoY growth rate can be used to examine how investors respond to mandated monthly revenues.[4] Moreover, revenues and products often exhibit

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[1]https://www.bloomberg.com/news/articles/2024-03-08/tsmc-s-sales-gain-9-4-in-first-two-months-after-ai-boost?

[2]Post-earnings-announcement drift (PEAD) has been documented, challenging 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]For example, according to a CNBC report on November 21, 2023, Nvidia's revenue grew 206% year over year during the quarter ending Oct. 29. Link: https://www.cnbc.com/2023/11/21/nvidia-nvda-q3-earnings-report-2024.html.

[4]We also use the standardized unexpected revenue growth (Jegadeesh and Livnat (2006), Chen and Yu (2022)) to estimate revenue momentum. In terms of the persistence and profitability of revenue momentum, YoY revenue growth is at least as effective as standardized unanticipated revenue growth.

specific monthly or seasonal patterns (Marks and Shang (2023)). For example, tourism and sunny weather may induce a spike in a restaurant's revenue during the summer. If investors only analyze month-over-month growth for June through August, they will observe rapid growth, potentially leading them to be over-optimistic. YoY growth is a simple and intuitive method to reduce the influence of seasonal revenue fluctuations on investment decisions.

The most frequent financial reports available in most stock markets are quarterly. Because quarterly financial reports aggregate 3 months of information, any exogenous shocks occurring within the quarter cannot be easily detected in these financial statements. Moreover, the time between the end of the calendar quarter and the date of filing the report is too long to determine whether the market experiences surprises or is affected by other news. Therefore, higher-frequency data provide more reliable information indicating how investors respond to financial announcements regarding top-line performance. The Taiwan Stock Exchange is exceptional in requiring publicly traded firms to announce operating revenue for the preceding month by the 10th day of each calendar month. Using this interim data, we can partially mitigate the problem of insufficient information in quarterly financial reports and examine whether the market incorporates interim information into the stock price.[5]

Our results can be summarized as follows. First, we document substantially positive profits from revenue momentum because stocks with high RG earn higher future returns than stocks with low RG. The equally weighted (value-weighted) Fama–French three-factor alpha is 0.886% (0.698%). Using this strategy, $1 invested at the beginning of

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Additionally, the average cross-sectional correlation coefficient between these two measures is 0.55, suggesting a strong correlation. Hence, despite its simplicity, YoY revenue growth effectively represents the element of surprise in revenue growth. The results are available from the corresponding author upon request.

[5]Refer to Appendix B for information on the composition of the Taiwan stock market.

1990 grows into \$21 and \$8 after 29 years for equally weighted and value-weighted portfolios, respectively. Second, the profitability of revenue momentum is not caused by significant characteristics, such as the price-to-book ratio, beta, turnover ratio, momentum, or short-term reversals.[6] The results of our analysis suggest that RG may explain stock returns in the Taiwan stock market as much as the aforementioned variables.

Because mandated monthly revenue reports are unaudited and lack supplementary details, whether investors underreact to this highly uncertain information is poorly understood. Nevertheless, Jegadeesh and Livnat (2006) suggest that revenues tend to be highly persistent. Consistent with this observation, we demonstrate that stocks with high RG in a given month are likely to have high RG in the following month. In total, 64.27% (64.41%) of stocks in the top (or bottom) RG portfolio have the same rank in the following month as in the preceding month compared with a randomly distributed percentage of 33%. Moreover, we extend the holding periods of portfolios generating revenue momentum from 1 month to multiple months to evaluate the effectiveness of 1-month revenue information on future stock returns. As the holding period increases, the predictive power of RG on stock returns declines as the new RG information in the portfolio decays. Hence, investors underreact to stocks with persistently high RG.

We capture persistent RG by sorting stocks into strongly persistent and weakly persistent portfolios. Strongly persistent portfolios contain stocks with consistent lagged one- and two-period ranks. Weakly persistent portfolios contain stocks with substantial changes in RG portfolio ranks over months $t-1$ and $t-2$. The results indicate that persistence considerably strengthens revenue momentum. Additionally,

[6] Revenue momentum remains strong across subperiods, such as those defined by January effects, international financial reporting standards adoption, investor sentiment, market return, and business cycles. These unreported results are available from the corresponding author upon request.

portfolios with strongly persistent revenue momentum substantially outperform portfolios with weakly persistent revenue momentum. The difference in equally weighted (value-weighted) risk-adjusted returns between portfolios with strongly persistent and weakly persistent revenue momentum is 1.030% (0.571%) per month with a *t* statistic of 3.33 (1.78), indicating that RG persistence strengthens revenue momentum.

If a stock exhibits persistently high RG, why do investors not pay a higher price for it? Is this mispricing due to the limits of arbitrage or to cognitive bias? That is, is the mispricing the result of rational or irrational investor behavior? We examine why investors incorrectly evaluate the possibilities of RG persistence using four arbitrage cost measures: market capitalization (Brav et al. (2010)), illiquidity ((Chordia et al. (2009)), relative bid–ask spread (Ng et al. (2008)), and idiosyncratic volatility (Mendenhall (2004)). Additionally, we adopt three attention bias measures: the 52-week high ratio, the recency ratio, and information discreteness.[7]

George et al. (2015) indicate that underreaction to accounting fundamentals, such as unexpected earnings, is associated with anchoring on the 52-week high. Goh and Jeon (2017) observe that the effect of post-earnings-announcement drift (PEAD) is more pronounced when stocks near their 52-week highs, potentially due to the anchoring bias. Byun et al. (2020) further suggest that investors consider the 52-week

[7]George and Hwang (2004) indicate that investors use the 52-week high (H52) as an anchor when assessing stock price. Because investors overemphasize the anchor (anchoring bias), they underreact to positive (or negative) news regarding stocks with prices are near to (or far from) their H52. For example, when positive 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 available information warrants such bidding. Hence, they underreact to positive news. When the information eventually prevails and the price increases, momentum is generated. Bhootra and Hur (2013) propose that the anchoring bias is stronger for stocks with recent H52s than stocks with distant H52s. Following Bhootra and Hur (2013), we construct a recency ratio to measure the distance to the most recent H52. Da et al. (2014) document that investors are inattentive to information that arrives continually 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 positive daily returns relative to negative daily returns to estimate information discreteness that captures the relative frequency of small signals.

high as the upper price limit and demonstrate that this information acts as a psychological barrier against investing in lottery-like stocks.[8]

We discover that the profitability of strongly persistent revenue momentum is not entirely driven by arbitrage cost and behavioral bias variables. Specifically, the profitability of strongly persistent revenue momentum is substantially positive across stocks, regardless of their classification according to arbitrage cost or behavioral bias variables. Additionally, consistent with the arbitrage cost hypothesis, investors exhibit a greater underreaction to stocks with more persistent RG and higher arbitrage costs.

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 available, indicating that the interim earnings information is incorporated into the stock price. Hence, we test whether quarterly revenue information has been incorporated into the stock price when monthly revenue is announced. The results reveal that quarterly revenue announcement drift is absent after controlling for monthly revenue. By contrast, revenue momentum based on monthly revenue remains after quarterly revenue is controlled for. This finding suggests that monthly revenue reports dominate the information in quarterly revenue announcements, consistent with the finding of DeFond et al. (2007).

This study makes several contributions to the literature. First, although financial news outlets frequently report YoY RG rates, research discussing the predictive power of YoY growth rates for stock returns is lacking. This study fills this gap. Second, studies have proposed momentum strategies on the basis of quarterly financial information (Jegadeesh and Livnat (2006), Chen et al. (2014)). The present study is the

[8]Tversky and Kahneman (1992) indicate that investors hold cognitive illusions regarding probabilities, tending to overweight small probabilities and underweight large probabilities.

first to demonstrate that monthly revenue momentum is statistically significant in predicting stock returns. Additionally, monthly revenues clarify the information available prior to the release of quarterly financial reports. Nevertheless, the mandated monthly revenue reports of the Taiwan Stock Exchange are unaudited and lack supplementary details, and investors may adopt conservative strategies when accessing them. We design a measure that helps investors clarify the information in monthly revenue reports. We reveal that stocks with robust RG (consecutive growth over 2 months) earn substantially positive returns, whereas stocks with nonconsecutive RG do not. Finally, although underreaction to stocks with low arbitrage costs is not uncommon, such underreaction is more pronounced for stocks with high arbitrage costs. This study is structured as follows. Section 2 outlines the data used, Section 3 presents analyses of portfolio revenue momentum, Section 4 analyzes persistent RG, and Section 5 presents the Conclusions.

2. Data and variables definitions

We obtain the daily and monthly stock prices, market (TAIEX) returns (including dividends), and other stock trading and accounting data, such as monthly operating revenues and the number of outstanding shares, from the commercial database maintained by the *Taiwan Economic Journal* (*TEJ*) for the period from January 1990 to December 2019.[9] The sample excludes stocks in the financial industry (*TEJ* two-digit standard industrial classification code = 28). The final total of month-stock observations is 182,902. RG is defined as the YoY growth rate of operating revenue from the same calendar month of the previous year to capture investor reactions to monthly announcements of operating revenue. By the 10th day of each calendar month, each

[9]We limit the sample to the end of December 2019 to avoid the confounding effect of the pandemic on revenues in 2020, as suggested by an anonymous reviewer. We exclude over-the-counter stocks because they have low liquidity and high trading costs.

listed firm is required to announce its operating revenue for the preceding month. The variables used are defined in Appendix A. Information on the Taiwan Stock Exchange is presented in Appendix B.

Table 1 presents descriptive statistics on the firms examined in this study. The average RG of our sample is 13.00%, and the median RG is 3.11%, indicating that the RG distribution is right-skewed. The data in Panel B indicate that the RG has moderate correlations with other stock characteristics, with the highest being 0.18 between RG and the previous 12-month return. The results suggest that because of the low correlation between revenue growth and well-documented variables, such as market capitalization, price-to-book ratio, momentum, and illiquidity, the revenue growth could be an essential factor to help explain stock returns in the Taiwan Stock Exchange.

[Table 1 here]

3. Revenue momentum

3.1. Portfolio analysis

To mitigate the influence of the look-ahead bias, for each stock at the end of month t, we sort all stocks into portfolios groups on the basis of the RG in month $t-1$. The portfolios are held for 1 month ($t+1$), and portfolio returns are equally and value-weighted. Revenue momentum is calculated as 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. This argument suggests that the superior performance of stocks with high RG may indicate that such stocks are likely to be exposed to systematic risk. To 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):

$$r_{p,t} = a_p + b_p MKT_t + s_p SMB_t + h_p HML_t + e_{p,t}, \quad (1)$$

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 book-to-market (B/M) effects, respectively, and a_p is the intercept term of the regression model. 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 systematic risk factors.[10] The performance of the portfolios is measured by the raw returns and Fama–French (1993) alphas.

The data presented in Panel A of Table 2 indicate that the equally weighted (value-weighted) revenue momentum return (the zero-investment portfolio raw returns between the high and low RG portfolios) of 0.852% (0.653%) is significantly positive. The corresponding equally weighted (value-weighted) Fama–French three-factor alpha is 0.886% (0.698%), which is significant at the 1% level. These results indicate that the correlation between RG 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 (or value-weighted) returns of a zero-cost portfolio primarily result from the long leg of the high RG portfolio. Panel B of Table 2 presents the mean characteristics for each of the three RG portfolios. Stocks with high

[10]Following Fama and French (1993), HML and SMB portfolios are constructed as follows. At the beginning of each July from 1989 to 2019, all stocks are allocated to two size groups (S and B) on the basis of whether their June market equity is below or above the median market equity. Subsequently, all stocks are independently allocated to three B/M groups (L, M, and H) on the basis of the breakpoints for the bottom 30%, middle 40%, and top 30% of the values of the B/M portfolio. Six size/B/M portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are constructed from the intersections of the two size and three B/M groups. The value-weighted returns of these groups are calculated from July to the next June, the first 12 months after formation. The return on the HML portfolio is calculated as 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, and the return on the SMB portfolio is calculated as 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.

RG tend to have high market capitalization, high price-to-book ratio, high turnover, high beta, high idiosyncratic volatility, low illiquidity, low bid–ask spread, high prior 1-month return, and high momentum. In the following sections, we explore whether these variables drive returns in RG portfolios.

The results depicted in Figure 1 reveal that from January 1990 to December 2019, 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. In concrete terms, $1 invested at the beginning of 1990 will grow into $21 and $8 after, respectively, after 29 years for equally weighted and value-weighted portfolios, respectively.

[Table 2 here]

[Figure 1 here]

3.2. Revenue momentum conditional on stock characteristics

To confirm the RG effect, we form two-dimensional sequentially sorted portfolios on the basis of stock characteristics and RG. First, we classify stocks into three portfolios by stock characteristics. Second, we divide stocks into three RG subportfolios within each characteristic portfolio. These portfolios are held for 1 month. The raw returns and the returns adjusted for the three Fama–French factors are calculated. We present the average zero-cost RG portfolio returns across the three subportfolios (sorted from low to high) for each characteristic. The definitions of firm characteristics are detailed in Appendix A.

Because arbitrage is costly, the mispricing of stocks may persist for longer when the limits to arbitrage are more severe. We use the following stock characteristics as proxies for limits to arbitrage: market capitalization illiquidity (Amihud (2002)), relative bid–ask spread, and idiosyncratic volatility. Table 3 presents the average zero-cost RG portfolio returns across the three portfolios for each stock characteristic. The raw and abnormal returns on the zero-cost RG portfolio are all significantly positive at the 1% level for each stock characteristic. This result suggests that the RG portfolio returns cannot be explained by the aforementioned variables used to measure the limits to arbitrage. In addition to the four proxies for limits to arbitrage, we include beta, price-to-book, prior 1-month returns, and prior 12-month returns in our robustness test. Overall, we observe similar results across firm characteristics, indicating that our results are robust to the major variables that determine stock returns.

[Table 3 here]

3.3. Quarterly revenue announcements and monthly revenue momentum

Most studies analyze quarterly financial reports because they are the earliest information available. Nevertheless, these reports aggregate 3 months of information, making it challenging to precisely detect exogenous shocks occurring within a quarter. Additionally, the long period between the end of the calendar quarter and the report filing date complicates the determination of whether the market is influenced by unexpected results or other news. DeFond et al. (2007) suggest that the market reaction to less frequent financial reporting, such as annual earnings, weakens when more frequent interim financial reporting occurs, indicating that stock prices incorporate earnings information. Taiwan is currently the only country that mandates firms to disclose the preceding month’s operating revenues by the 10th day of each calendar month. Using this monthly revenue data can partially alleviate the problem of shocks affecting stock returns within a quarter and assist in examining whether the market integrates this interim information into stock prices. Specifically, we test whether stock prices incorporate the high-frequency monthly RG data by the time quarterly information is released.

For the period from January 1990 to December 2019, we form two-dimensional sequentially sorted portfolios for each month *t* on the basis of a stock's RG and calculate standardized unexpected revenues (SUR) on the basis of the most recently announced quarterly revenues (as defined in Appendix A). Initially, we categorize stocks into three portfolios according to RG. Subsequently, we divide stocks into 10 SUR subportfolios within each RG portfolio. As indicated in Panel A of Table 4, the (High – Low) SUR portfolio yields insignificant raw and risk-adjusted returns for stocks with low and high RG. This result suggests that high-frequency monthly revenue announcements are more influential to stock returns than low-frequency quarterly revenue announcements.

We also form two reverse two-dimensional sequentially sorted portfolios on the basis of a stock's SUR and RG. As indicated in Panel B of Table 4, the (High – Low) RG portfolio is significantly positive for stocks with low or high SUR. Hence, the quarterly SUR is not more influential than the monthly revenue announcements, suggesting that monthly RG information dominates quarterly earnings announcements. This finding is consistent with that of DeFond et al. (2007) indicating that the price of stocks on the Taiwan Stock Exchange incorporates information from monthly revenues by the time quarterly revenues are released.[11]

[Table 4 here]

4. Persistence in RG

[11]We also calculate the dummy ordinary least squares regression of the Fama and French three-factor model to determine risk adjusted returns. The dummy equals 1 in months when quarterly financial reports are disclosed (May (Q1), August (Q2), November (Q3), and April (Q4)) and 0 otherwise. We exclude monthly information that overlaps months in which quarterly reports are released, such as that for April, May, August, and November, to determine whether monthly revenue momentum remains profitable. We further explore whether months with quarterly financial reports enhance or distort the monthly revenue momentum. The results of our analysis reveal that first, the revenue momentum has a significantly positive alpha during nonreporting months. Second, the profits for months with quarterly reports are substantially higher than those for months when quarterly information is not reported, suggesting that quarterly financial reports substantially increase profits of monthly revenue momentum. These unreported results are available from the corresponding author upon request.

4.1. New revenue information and revenue momentum

Portfolio ranks at the end of month t are calculated on the basis of RG in month $t - 1$, and portfolio returns are calculated in month $t + 1$. In the holding month $t + 1$, the operating revenue of month t is filed by the 10th day of the month. Hence, newly announced revenue may affect the returns of the portfolio. Figure 2 illustrates the lead-lag relation across portfolio formation, holding, and operating revenue announcement dates.

[Figure 2 here]

We use persistent RG rank as a proxy for RG persistence. We examine the extent to which stocks with the highest (or lowest) RG in month t also have the highest (or lowest) RG in the subsequent month. We analyze the percentage of stocks with unchanged ranks during 2 consecutive months. The data presented in Table 5 reveal that 64.27% (64.41%) of stocks in the top (or bottom) RG portfolio have the same rank in the following month. Compared to a randomly distributed percentage of 33%, our results indicate that the RG portfolio exhibits high RG persistence. These results are consistent with the finding of Jegadeesh and Livnat (2006) that revenues tend to be persistent.

[Table 5 here]

We subsequently extend the holding periods of the RG portfolio presented in Table 2 to 36 months to examine whether the RG information predicts long-term RG. From January 1990 to December 2019, at the end of each month t, we use lagged RG (month $t - 1$) to sort all stocks into three portfolios: the highest portfolio (H) contains stocks in Group 3, the lowest portfolio (L) contains stocks in Group 1, and all other stocks are placed in the medium (M) portfolio (Group 2). The zero-cost portfolio (indicative of revenue momentum) is constructed by long-buying the highest RG stocks and short-selling the lowest RG stocks. The portfolios are held from 1 to 36 months and rebalanced each month. The overlapping portfolio returns are equally weighted. Figure 3 illustrates the reversal pattern of revenue momentum for the extended post-formation periods. These portfolio returns rapidly dissipate. As the holding time increases, the predictive power of RG information soon decays. This deteriorating revenue momentum suggests that the RG information released in month t loses relevance over time.

[Figure 3 here]

4.2. Predictive ability of persistency

Our results from the preceding analysis suggest that persistence in portfolio ranks is crucial to revenue momentum. In the following analysis, we test whether past RG rank persistence predicts RG rank persistence in later months.

We conduct a portfolio analysis by independently double sorting all stocks into nine (three × three) portfolios on the basis of lagged one-period and lagged two-period RG. Specifically, at the end of month t, we sort all stocks into three portfolio ranks on the basis of RG in month $t-1$ (the lagged one-period RG portfolio). At the end of month $t-1$, we sort all stocks into three portfolio ranks on the basis of RG in month $t-2$ (the lagged two-period RG portfolio). Strongly persistent and weakly persistent portfolios are constructed from the intersections of the three lagged one-period RG portfolios and three lagged two-period RG portfolios. The strongly persistent groups contain stocks with the same lagged one and lagged two-period portfolio rank, and the weakly persistent groups contain stocks with the largest changes in RG portfolio ranks during months $t-1$ and $t-2$. For example, the portfolio $\text{Low}_{\text{strong}}$ contains stocks with the lowest portfolio rank during months $t-1$ and $t-2$.

The results presented in Table 6 reveal that revenue momentum is primarily driven by persistence in RG ranks. When we separate stocks into strongly persistent and weakly persistent subportfolios, the weakly persistent revenue momentum subportfolio yields insignificant returns, whereas the strongly persistent revenue momentum subportfolio yields positive and significant returns of 1.061% and 0.764% for equally weighted and value-weighted raw returns, respectively. Furthermore, the strongly persistent revenue momentum subportfolio considerably outperforms the weakly persistent revenue momentum subportfolio. The equally weighted (value-weighted) raw spread between the strongly persistent and weakly persistent revenue momentum subportfolios is 0.924% (0.479%) per month with *t* statistics of 2.83 (1.66). The Fama–French three-factor alphas for the difference between the strongly persistent and weakly persistent revenue momentum subportfolios are also significantly positive. These results suggest that past persistence in RG ranks predicts persistence in RG ranks, or newly announced revenue information, which leads to positive revenue momentum returns.[12]

[Table 6 here]

To determine whether volatile revenue reduces profits from revenue momentum, we estimate the following George and Hwang (2004) cross-sectional regressions to compare strongly persistent, weakly persistent, and traditional revenue momentum:

[12] We also use three lags to define strongly and weakly persistent stocks. The strongly and weakly persistent portfolios are constructed from the intersections of the three lagged one-period RG portfolios, three lagged two-period RG portfolios, and three lagged three-period RG portfolios. The strongly persistent groups contain stocks with the same lagged one-period, lagged two-period, and lagged three-period portfolio rank. The weakly persistent groups contain stocks with the highest (or lowest) lagged one-period portfolio rank and the lowest (or highest) ranks of the lagged two-period and three-period portfolios. These unreported results indicate that stronger persistence in revenue growth is correlated with higher the RG momentum profits. The larger lags of persistence increase the profits from persistent revenue momentum. However, excessive lags also reduce the number of stocks in each portfolio. These results are available from the corresponding author upon request. We appreciate the suggestions of an anonymous reviewer to limit portfolio sorting to three-ranks to avoid skewing the results from the extreme performance of a few stocks in a given portfolio.

$$R_{i,t} = \beta_{0,t} + \beta_{1,t}SGH_{i,t-2} + \beta_{2,t}SGL_{i,t-2} + \beta_{3,t}SGH_{i,t-2} \cdot SPH_{i,t-2} + \beta_{4,t}SGL_{i,t-2} \cdot SPL_{i,t-2} + \beta_{5,t}SGH_{i,t-2} \cdot WPH_{i,t-2} + \beta_{6,t}SGH_{i,t-2} \cdot WPL_{i,t-2} + c_t CONTROL_{t-1} + e_{i,t}, \tag{2}$$

where R_{it} is the return of stock *i* in month *t*; $SGH_{i,t-2}$ equals 1 if stock *i*'s traditional SG is in the top 33% when measured and 0 otherwise; $SGL_{i,t-2}$ equals 1 if stock *i*'s traditional SG is in the bottom 33% and 0 otherwise. SG is defined as traditional RG momentum, strong persistence (SP) is defined as strongly persistent RG momentum, and weak persistence (WP) is defined as weakly persistent RG momentum. SGHs are defined as traditional winner stocks; SGLs as traditional loser stocks; SPHs as strongly persistent winner stocks; SPLs as strongly persistent loser stocks; WPHs as weakly persistent winner stocks; and WPLs as weakly persistent loser stocks. CONTROL refers to the control variables defined in Appendix A. We construct an interaction term between the original RG and strongly (or weakly) persistent RG for the high and low portfolios to explore the incremental contribution of strongly (or weakly) persistent RG to SG. For example, if the coefficient of the interaction term SGH*SPH is significantly greater than 0, the performance of SPH stocks within the SGH portfolio is superior to that of stocks in the original SGH portfolio, and vice versa. SG is defined as the difference between SGH and SHL. SP is defined as the difference between the interaction terms SGH*SPH and SGL*SPL. WP is defined as the difference between the interaction terms SGH*WPH and SGL*WPL.

Because disclosure on revenue trends is more relevant for technological firms than for utility companies with a stable and predictable revenue pattern, the underreaction to persistent RG may be stronger for stocks in the technology sector. Similarly, because the information on monthly revenue is unaudited, the reliability of accounting data should be higher for firms audited by the Big 4 firms than for firms audited by non-Big-4 auditors. We examine whether the market reaction differs between technological versus nontechnological sectors and between firms audited by Big 4 versus non-Big-4 auditors.

The results indicate that the performance of the monthly revenue strategy is influenced by RG persistence (Table 7). First, after controlling for the variables of interest, the SG strategy remains profitable. Second, the significant and positive coefficient of the interaction term SGH*SPH indicates that SPH stocks outperform SGH stocks. Third, SPL stocks do not substantially underperform SGL stocks. Hence, the observed increase in revenue growth is primarily contributed by SPH stocks. Fourth, the significant and negative coefficient of the interaction term SGH*WPH suggests that WPH stocks perform substantially worse than SGH stocks, whereas WPL stocks do not substantially underperform SGL stocks. Consequently, the observed performance weakening due to revenue fluctuations must originate from the WPH stocks. Finally, the coefficient of WP measures the difference between SGH*WPH and SGL*WPL. The negative WP coefficient of −0.763 indicates that WP performs considerably worse than SG, whereas the SP coefficient of 0.360 indicates that SP substantially outperforms SG.

Overall, this evidence underscores the importance of revenue information consistency to stock performance, particularly for revenue winners. The more drastic the changes between the two periods' RG ranks are, the greater is the negative effect on the strategy's performance. Additionally, the strategy's performance can be considerably improved by refining the SG strategy and excluding the stocks with the most drastic changes in RG ranking between the two periods. Furthermore, we separate the sample into technology and nontechnology industries and those audited by the Big

4 and those not by the Big 4, to determine whether differences exist between these groups. The results reveal that the outcomes for technology and nontechnology industries and Big 4 and non-Big-4 auditor groups are similar, with significant RG momentum effects. Therefore, the revenue momentum effect is likely not influenced by industry or auditor grouping.[13]

[Table 7 here]

4.3. Explanations of underreaction to persistence in RG

Studies have suggested 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)). Moreover, these anomalies may 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 the factors that explain the potential investor underreaction to possibilities of persistency in RG.

The first category of variables is associated with attention bias, and the other is associated with arbitrage costs. The attention bias variables comprise the 52-week high (George and Hwang (2004)), recency ratio (Bhootra and Hur (2013)), and information discreteness (Da et al. (2014)).[14] The arbitrage cost variables are market capitalization, illiquidity, relative bid–ask spread, and idiosyncratic volatility. The detailed definitions of the three attention bias variables are presented in Appendix A. From January 1990 to December 2019, for each month *t*, we form two-dimensional sequentially sorted portfolios. First, we separate stocks into three groups using stock control variables. Second, within each control group, we independently sort stocks into three portfolio

[13]We appreciate the feedback from an anonymous reviewer for these suggestions.
[14]Following Hung et al. (2022), we use these three variables as proxies for attention bias.

ranks on the basis of RG in month $t-1$ (lagged one period) and three portfolio ranks on the basis of RG in month $t-2$ (lagged two periods). Within each control group, the strongly persistent portfolios are constructed from the intersections of the three lagged one-period RG portfolios and three lagged two-period RG portfolios. The strongly persistent portfolios contain stocks with the same lagged one-period and lagged two-period portfolio rank. We test whether attention or arbitrage cost variables affect investors' reactions to RG, reporting the value-weighted raw returns and Fama–French alphas.[15]

The data presented in Panel A of Table 8 reveal that all stocks with strongly persistent revenue momentum experience significant and positive returns associated with the four arbitrage cost control variables. Consistent with the arbitrage cost hypothesis, the underreaction to RG persistency for stocks with high arbitrage costs is statistically larger than for those with low arbitrage costs. Specifically, stocks with high arbitrage costs (low market capitalization, high illiquidity, and high idiosyncratic volatility) have higher risk-adjusted returns from strong revenue momentum than those with low arbitrage costs.

George and Hwang (2004) demonstrate that investors use a 52-week high price as a reference point in their decision-making process. Investors are typically reluctant to bid up the price of stocks that trade near their 52-week high, even if 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 suggest that anchoring on the 52-week high—but not unexpected earnings—drives the market's underreaction to extreme earnings news. Goh and Jeon

[15]For the sake of brevity, we provide only the value-weighted results. The equal-weighted results are quantitively similar and are available from the corresponding author upon request.

(2017) document that the PEAD effect is particularly pronounced when stocks trade near their 52-week highs, possibly due to the anchoring bias. Byun et al. (2020) also report that the overpriced lottery anomaly is present primarily among stocks far from their 52-week high prices. Hence, mispricing is associated with how near the stocks are to their 52-week highs. The data presented in Panel B of Table 8 indicate that the profits from strongly persistent revenue momentum do not significantly differ when assessed using high or low attention bias variables. Although the sign of the difference in strongly persistent revenue momentum is consistent with the psychological bias hypothesis, the underreaction to strongly persistent RG is statistically similar across attention variables.

These results indicate that investors may not fully consider the potential for persistent RG because of arbitrage constraints. High risks associated with arbitrage, high trading costs, and substantial market impact costs may explain why revenue momentum is stronger in stocks with higher arbitrage costs.

[Table 8 here]

5. Conclusions

Adopting the unique dataset of monthly operating revenues from stocks on the Taiwan Stock Exchange from the *TEJ* database, we document substantially positive profits resulting from revenue momentum, demonstrating that stocks with high YoY RG earn higher future returns than stocks with low YoY RG. This revenue momentum is robust to arbitrage cost variables and is not driven by price-to-book ratio, beta, turnover ratio, previous 1-month returns, previous 12-month returns, or other variables that predict cross-sectional stock returns. This revenue momentum is also not the result of quarterly revenue announcement drift. However, monthly revenue strongly influences quarterly revenue announcements, suggesting that stock prices incorporate monthly revenue information before quarterly revenues are released.

Our findings suggest that the positive profits of revenue momentum are primarily driven by persistence in RG. Stocks with persistently high RG are likely to have high RG in consecutive months. Additionally, revenue momentum exhibits a reversal pattern during extended holding periods. The profits of overlapping revenue momentum rapidly dissipate in the short term. As the length of the holding period increases, the predictive power of past RG information on RG information rapidly declines, as does revenue momentum. Finally, prior persistence substantially increases revenue momentum.

We also demonstrate that investors underreact to the possibility of persistent RG, especially in stocks with substantial arbitrage restrictions. Moreover, trading frictions may limit the potential profits from persistent RG. Specifically, stocks with high arbitrage costs (low market capitalization, high illiquidity, and high idiosyncratic volatility) have higher risk-adjusted returns from strong revenue momentum than those with low arbitrage costs. This finding suggests that market efficiency may be constrained in these scenarios because trading frictions and arbitrage costs adversely influence investors' responses to information.

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 the top and bottom 1% in distribution.
2. Size (MV, millions)
   MV is defined as the market value of equity at the month-end prior to portfolio formation.
3. Price-to-book equity (PB)
   PB is defined 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 1-month Bank of Taiwan deposit rate on the daily returns to the common factors associated with market, size, and book-to-market ratio. We require a minimum of 15 observations for model estimation.
5. Systematic risk (BETA)
   We estimate BETA by regressing daily excess returns on market risk premium for each firm and month.
6. Prior returns (PR01)
   PR01 is defined as the 1-month return of a firm at the month-end prior to portfolio formation.
7. Prior returns (PR12)
   PR12 is defined as a firm's 12-month return (not including the most recent month) at the month-end prior to portfolio formation.
8. Turnover (TURN)
   TURN is defined as the ratio of monthly trading volume to shares outstanding at the month-end prior to portfolio formation.
9. Illiquidity (ILQD)
   Amihud (2002) defined illiquidity as the average ratio of the daily absolute return to the dollar trading volume on that day. This measure is multiplied by 10^6.
10. Relative bid–ask spread (BASK)
    BASK is defined as the average ratio of the 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 a stock's current price to the maximum price in the previous 12 months (not including the most recent month).
12. Recency ratio (RR)
    RR is defined as 1 − (number of days since 52-week high price)/364.
13. Information discreteness (ID)
    ID = sgn(PRET) × [%neg −%pos], where PRET is the cumulative return during the formation period. sgn(PRET) is the sign of PRET. sgn(PRET) = 1 if PRET > 0 and sgn(PRET) = −1 if PRET < 0. %neg and %pos are the percentages of days during the formation period with positive and negative returns.
14. Standardized unexpected revenues (SURs)
    SUR = $(QSPS_t - QSPS_{t-4})/\sigma_t$, where $QSPS_t$ is the most recently announced quarterly revenues per share and σ_t is the standard deviation of $(QSPS_t - QSPS_{t-4})$ over the prior eight quarters.

Appendix B. The Taiwan Stock Exchange

The Taiwan Stock Exchange (TWSE) is characterized by high liquidity. At the end of 2019, 830 stocks were listed on the TWSE. The total market capitalization of TWSE-listed stocks at that time was approximately 1.5 trillion USD. The TWSE exhibits annual turnover rates that fluctuate between 78% and 120%, mitigating concerns related to illiquidity. A distinctive feature of the TWSE is that individual investors contribute to over 70% of its trading volume, whereas institutional investors predominate in most major world markets. The substantial presence of retail investors in the TWSE may lead to mispricing due to these investors' unpredictable trading behaviors.

The TWSE requires companies to file quarterly earnings reports no later than 45 days after the end of each calendar quarter (May 15th, August 14th, and November 14th, for Q1, Q2, and Q3, respectively), and fourth quarter (Q4) earnings no later than 3 months after the end of the fiscal year (March 31st of the following year). Additionally, by the 10th day of each calendar month, each listed firm is required to announce its operating revenue for the preceding month. Although these monthly revenue reports provide timely information to investors, this information is unaudited and reflects revenues alone without indicating other profitability or operational details typically reported in quarterly and yearly financial statements.[16]

[16]Information regarding the regulation governing reporting is provided on the following website (Article 3): https://www.selaw.com.tw/English/LawArticle/Index/78774?sysNumber=LW10819029&releaseDate=2011-10-13&__RequestVerificationToken=CfDJ8B_FDAKsdUlLmdPa-gc0uaC1op1PuYw2dbVXA-oQ_1zQEJ7jtsliDNOezgOfPz4TuP56kp0TWgItCcGhh0DaG3xWSZzC0Ifx-V4xA6a0nokpvj5J5_dZVFR5GlpHw6xBuZINV56WlyiWRYqaB_DgmJU.

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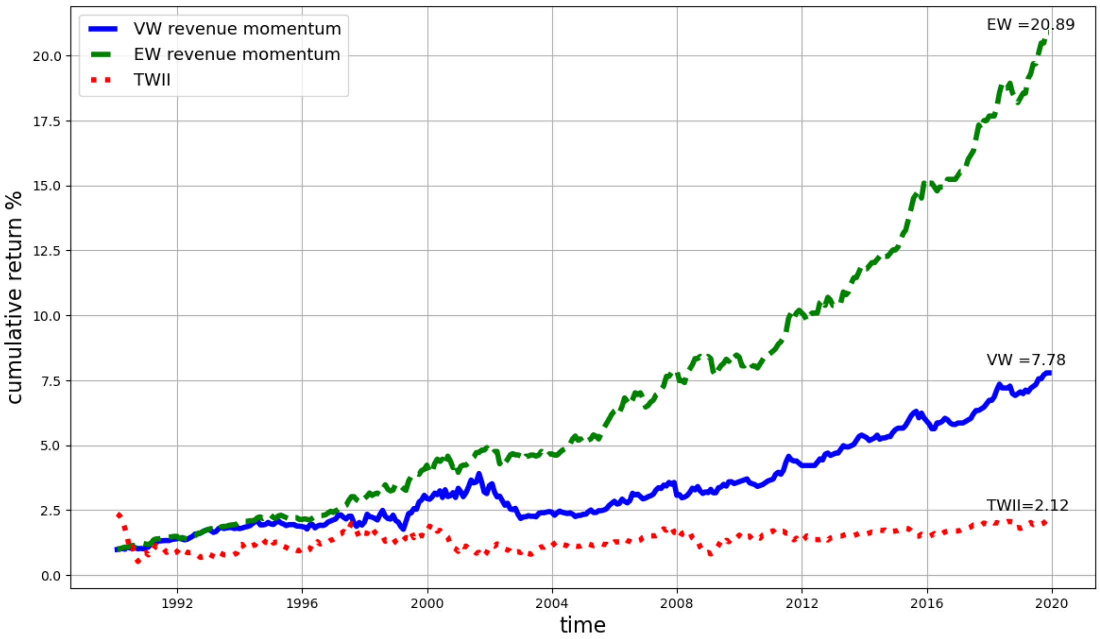

Figure 1. Cumulative returns of revenue momentum

Cumulative returns for equally-weighted (EW), value-weighted (VW) revenue momentum, and market return on the Taiwan Stock Exchange (TWII).

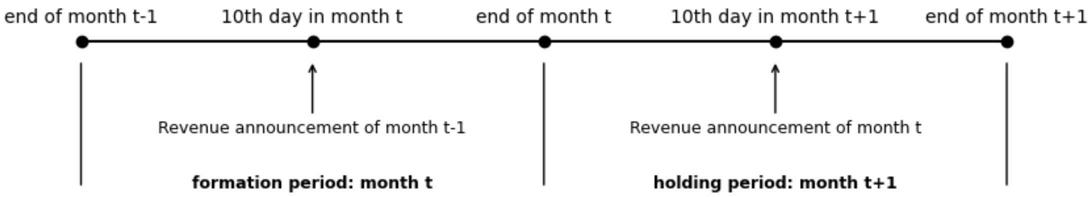

Figure 2. Timeline of portfolio formation and announcements of monthly revenue

Lead-lag relation across portfolio formation, holding, and operating revenue announcement dates.

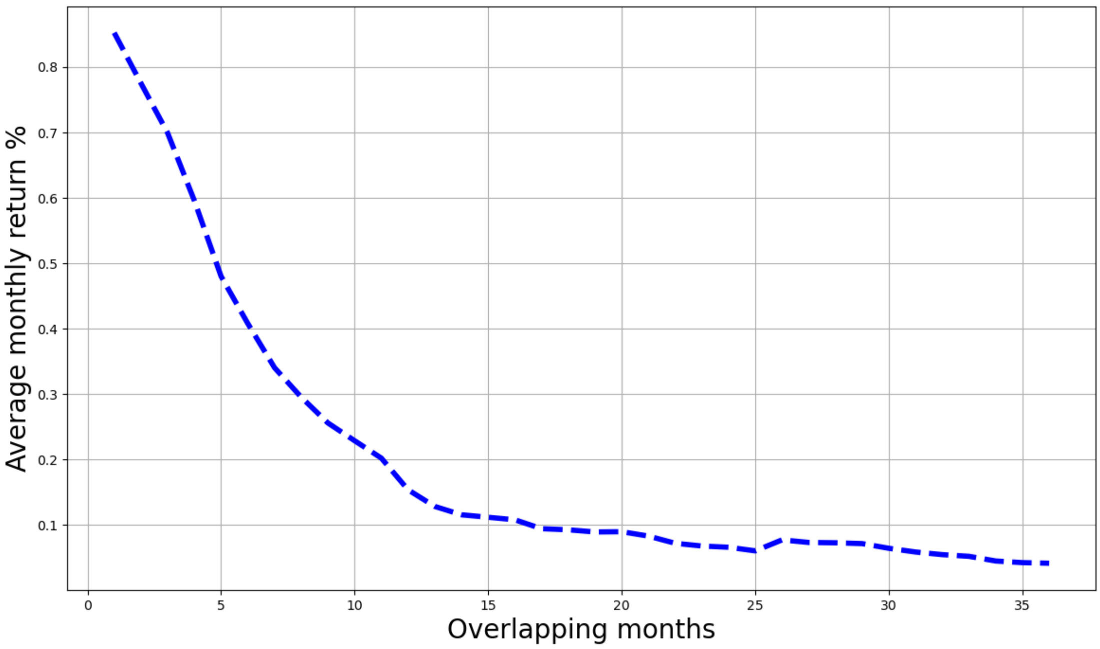

Figure 3. Overlapping returns on revenue momentum in each month following the formation period

From January 1990 to December 2019, at the end of each month t, we use revenue growth (RG) in month $t-1$ to sort all stocks into three groups. The highest portfolio contains stocks in Group 3, and the lowest portfolio contains the stocks in Group 1; all other stocks are placed in Group 2. The revenue momentum is constructed from the portfolio that long-buys the stocks with the highest RG and short-sells the stocks with the lowest RG. The portfolios are held from 1 to 36 months and rebalanced each month.

Table 1. Descriptive Statistics and Correlations among Firm Characteristics

Panel A presents the firm characteristics. The definitions of firm characteristics are presented in Appendix A. Panel B presents the Pearson correlations among variables. From January 1990 to December 2019, 182,902 month-stock observations are available.

Panel A: Summary statistics

	Mean	Std.	10^{th} pct.	Median	90^{th} pct.
RG (%)	13.00	64.33	-31.99	3.11	53.13
MV (NTD millions)	20636	65242	1144	5284	37160
PB	1.79	2.62	0.63	1.33	3.26
TURN (%)	16.37	23.99	1.25	7.63	41.70
BETA	0.77	0.69	0.03	0.74	1.56
IVOL (%)	1.56	0.84	0.63	1.40	2.69
ILQD	1.18	4.86	0.01	0.12	1.75
BASK (%)	0.47	0.48	0.16	0.37	0.82
PR01 (%)	1.00	12.94	-12.21	0.00	14.56
PR12 (%)	11.52	53.94	-37.11	2.28	65.87

Panel B: Pearson correlations

	RG	MV	PB	TURN	BETA	IVOL	ILQD	BASK	PR01	PR12
RG	1.00	0.02	0.07	0.08	0.03	0.05	-0.01	-0.01	0.00	0.18
MV		1.00	0.10	-0.06	0.07	-0.09	-0.07	-0.11	-0.02	0.04
PB			1.00	0.16	0.03	0.08	0.02	-0.02	-0.03	0.22
TURN				1.00	0.20	0.42	-0.13	-0.21	-0.04	0.32
BETA					1.00	0.15	-0.11	-0.15	-0.02	0.05
IVOL						1.00	0.14	0.19	-0.01	0.20
ILQD							1.00	0.52	0.04	-0.07
BASK								1.00	0.03	-0.07
PR01									1.00	0.00
PR12										1.00

Table 2. Revenue Momentum

Average returns (raw) and Fama and French three-factor adjusted returns (alphas) are reported. From January 1990 to December 2019, at the end of each month *t*, we use revenue growth (RG) in month $t - 1$ to sort all stocks into three portfolios. The high portfolio contains the stocks with the highest RG, and the low portfolio contains the stocks with the lowest RG. The revenue momentum is calculated as the difference in average returns between the stocks with the highest and lowest RG. The portfolios are held for 1 month and rebalanced each month, and the portfolio returns are either equally (EW) or value-weighted (VW). Panel B reports the average firm characteristics. Detailed definitions of the variables are presented in Appendix A. *t* statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Returns (%)

	Low	2	High	H-L
EW raw	0.437	0.858*	1.289***	0.852***
	(0.91)	(1.90)	(2.75)	(6.32)
EW FF alpha	-0.126	0.323***	0.760***	0.886***
	(-1.24)	(3.52)	(7.16)	(6.95)
VW raw	0.123	0.582	0.776*	0.653***
	(0.29)	(1.49)	(1.76)	(3.09)
VW FF alpha	-0.248*	0.241**	0.449***	0.697***
	(-1.84)	(2.24)	(3.04)	(3.42)

Panel B: Characteristics

RG (%)	-26.82	3.27	61.20	88.02
MV (millions)	15,868	22,937	23,247	7,379
PB	1.57	1.73	2.11	0.54
TURN (%)	14.06	14.55	20.58	6.52
BETA	0.74	0.75	0.81	0.07
IVOL (%)	1.58	1.45	1.64	0.06
ILQD	1.50	0.99	1.03	-0.47
BASK (%)	0.52	0.44	0.44	-0.08
PR01 (%)	-0.01	0.83	2.34	2.35
PR12 (%)	1.58	9.25	23.63	22.05

Table 3. Revenue Momentum Controlling for Stock Characteristics

For the period from January 1990 to December 2019, at the end of each month *t*, we form two-dimensional sequentially sorted portfolios on the basis of stock characteristics and revenue growth (RG). First, we separate stocks into three portfolios using stock characteristics. Second, we divide stocks into three RG portfolios within each characteristic portfolio. The average (high − low) RG portfolio returns are reported across the three control portfolios. Detailed definitions of stock characteristics are presented in Appendix A. *t* statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All numbers are percentages.

	MV	PB	TURN	BETA	IVOL	ILQD	BASK	PR01	PR12
EW Raw	0.892***	0.995***	0.909***	0.857***	0.895***	0.905***	0.806***	0.825***	0.867***
	(6.78)	(8.60)	(7.08)	(6.69)	(6.86)	(6.80)	(5.82)	(6.43)	(7.50)
EW FF alpha	0.924***	1.027***	0.958***	0.903***	0.933***	0.944***	0.867***	0.855***	0.891***
	(7.38)	(9.26)	(8.04)	(7.58)	(7.58)	(7.47)	(7.13)	(6.92)	(8.13)
VW Raw	0.799***	0.555***	0.723***	0.785***	0.722***	0.825***	0.554***	0.680***	0.691***
	(5.61)	(3.53)	(4.01)	(4.37)	(3.65)	(5.23)	(2.63)	(3.82)	(4.16)
VW FF alpha	0.834***	0.589***	0.779***	0.836***	0.772***	0.861***	0.619***	0.712***	0.711***
	(6.10)	(3.84)	(4.52)	(4.88)	(4.08)	(5.72)	(3.17)	(4.08)	(4.42)

Table 4. Quarterly Revenue Announcements and Monthly Revenue Growth

From January 1990 to December 2019, for each month *t*, we separate stocks into three portfolios on the basis of each stock's revenue growth (RG) (or standardized unexpected revenue [SUR]). Within each RG (or SUR) portfolio, we further divide stocks into three portfolios on the basis of SUR (or RG). Detailed definitions of SUR and RG are presented in Appendix A. *t* statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All numbers are percentages.

Panel A: First monthly RG, then quarterly SUR

	Low RG			High RG		
	Low SUR	High SUR	H-L	Low SUR	High SUR	H-L
EW Raw	0.222	0.307	0.085	0.910**	1.263***	0.353*
	(0.46)	(0.72)	(0.49)	(2.08)	(2.93)	(1.84)
EW alpha	-0.218	-0.100	0.118	0.499***	0.871***	0.372**
	(-1.38)	(-0.85)	(0.70)	(3.91)	(4.90)	(2.02)
VW Raw	0.190	-0.184	-0.374	0.716*	0.909**	0.193
	(0.41)	(-0.42)	(-1.14)	(1.80)	(2.01)	(0.57)
VW alpha	-0.203	-0.579***	-0.376	0.371*	0.552*	0.181
	(-0.82)	(-2.86)	(-1.13)	(1.68)	(1.94)	(0.55)

Panel B: First quarterly SUR, then monthly RG

	Low SUR			High SUR		
	Low RG	High RG	H-L	Low RG	High RG	H-L
EW Raw	0.151	0.831*	0.680***	0.474	1.339***	0.865***
	(0.29)	(1.94)	(3.40)	(1.20)	(3.09)	(5.14)
EW alpha	-0.317*	0.426***	0.743***	0.099	0.946***	0.847***
	(-1.84)	(3.43)	(3.97)	(0.78)	(5.36)	(5.34)
VW Raw	0.297	0.658*	0.361	0.132	1.084**	0.952***
	(0.59)	(1.91)	(1.05)	(0.34)	(2.21)	(2.73)
VW alpha	-0.117	0.345*	0.462*	-0.209	0.706**	0.915***
	(-0.40)	(1.89)	(1.71)	(-0.97)	(2.22)	(2.61)

Table 5. Transition Matrix of Revenue Growth

From January 1990 to December 2019, at the end of each month *t*, all stocks are sorted into three portfolios in ascending order of revenue growth (RG). For each portfolio, the table presents the time-series averages of the ratio of stocks in the given portfolio to those in the portfolio for month *t* + 1. All numbers are percentages.

		time t +1		
		Low	2	High
time t	Low	64.41	23.43	12.16
	2	23.66	53.22	23.12
	High	11.85	23.88	64.27

Table 6. Persistence and Revenue Momentum

Average raw returns and Fama and French three-factor adjusted returns (alphas) are reported. For the period from January 1990 to December 2019, at the end of each month t, we sort all stocks into three portfolio ranks on the basis of revenue growth (RG) in month $t-1$ (lagged one period). At the end of month $t-1$, we sort all stocks into three portfolio ranks on the basis of RG in month $t-2$ (lagged two periods). The strongly and weakly persistent portfolios are constructed from the intersections of the three lagged one-period RG portfolios and three lagged two-period RG portfolios. The strongly persistent groups contain stocks with the same lagged one- and two-period portfolio ranks. The weakly persistent groups contain stocks with the largest changes in RG portfolio rank during the months $t-1$ and $t-2$. For example, the portfolio $\text{Low}_{\text{strong}}$ contains stocks with the lowest portfolio rank during months $t-1$ and $t-2$. The strongly persistent revenue momentum portfolio ($\text{H-L}_{\text{strong}}$) is constructed by long-buying the persistently highest RG stocks and short-selling the persistently lowest RG stocks. The weakly persistent revenue momentum portfolio (H-L_{weak}) is constructed by long-buying the stocks with the highest weakly persistent RG and short-selling the stocks with the lowest weakly persistent RG. The spread is defined as the difference between $\text{H-L}_{\text{strong}}$ and H-L_{weak}. The portfolios are held for 1 month and rebalanced each month, and the portfolio returns are either equally (EW) or value-weighted (VW). t statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All numbers are percentages.

	Low_{weak}	$\text{High}_{\text{weak}}$	H-L_{weak}	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	$\text{H-L}_{\text{strong}}$	Spread
EW Raw	0.790*	0.927*	0.137	0.454	1.515***	1.061***	0.924***
	(1.66)	(1.75)	(0.54)	(0.92)	(3.25)	(5.78)	(2.83)
EW FF alpha	0.192	0.282	0.090	-0.178	0.941***	1.119***	1.029***
	(0.99)	(1.50)	(0.36)	(-1.44)	(7.56)	(6.57)	(3.33)
VW Raw	0.075	0.360	0.285	0.170	0.934**	0.764***	0.479*
	(0.17)	(0.70)	(0.93)	(0.38)	(2.09)	(3.03)	(1.66)
VW FF alpha	-0.396*	-0.134	0.262	-0.273*	0.561***	0.834***	0.572*
	(-1.74)	(-0.56)	(0.88)	(-1.68)	(3.39)	(3.45)	(1.78)

Table 7. Cross-Sectional Regressions

For the period from January 1990 to December 2019, following the recommendation of George and Hwang (2004), to compare profitability among strategies, we estimate the following cross-sectional regression:

$$R_{i,t} = \beta_{0,t} + \beta_{1,t}SGH_{i,t-2} + \beta_{2,t}SGL_{i,t-2} + \beta_{3,t}SGH_{i,t-2} \cdot SPH_{i,t-2} + \beta_{4,t}SGL_{i,t-2} \cdot SPL_{i,t-2} + \beta_{5,t}SGH_{i,t-2} \cdot WPH_{i,t-2} + \beta_{6,t}SGH_{i,t-2} \cdot WPL_{i,t-2} + c_t CONTROL_{t-1} + e_{i,t},$$

where R_{it} is the return of stock i in month t; $SGH_{i,t-2}$ equals 1 if stock i's traditional strong growth (SG) is in the top 33% and 0 otherwise; $SGL_{i,t-2}$ equals 1 if stock i's traditional SG is in the bottom 33% and 0 otherwise. SG is defined as traditional revenue growth (RG) momentum, SP as strongly persistent RG momentum, and WP as weakly persistent RG momentum. SGH refers to original winner stocks, SGL to original loser stocks, SPH to strongly persistent winners, and SPL to strongly persistent losers. WPH refers to weakly persistent winners, and WPL refers to weakly persistent losers. CONTROL refers to the control variables defined in Appendix A. We estimate the coefficient of a pure SG winner portfolio (b_1) as follows. The time-series average of the month-by-month coefficients and corresponding t statistics are calculated. We construct an interaction term between original RG and strongly (or weakly) persistent RG for high and low portfolios to explore the incremental contribution of strongly (or weakly) persistent RG to SG. For example, if the coefficient of the interaction term SGH*SPH is significantly greater than 0, the performance of SPH stocks within the SGH group is superior to that of those in the original SGH group, and vice versa. We use *Taiwan Economic Journal* (*TEJ*) industry codes to define whether a stock belongs to the technology industry. The sample period for the technology industry is restricted to the months after January 2000 because of the paucity of observations. We use *TEJ* audit data to define whether the Big 4 auditors audit a stock. The Big 4 auditors are Deloitte (code: KK157), PwC (code: KK149), KPMG (code: KK152), and EY (code: KK158). The sample period for the non-Big-4 stocks is also restricted to the months after January 2000 because of the paucity of observations available. Detailed definitions of the variables are presented in Appendix A. t statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All	Tech	Non-tech	Big4	Non-Big4
Intercept	0.601	1.303***	0.792**	0.634*	1.304***
	(1.64)	(3.67)	(2.15)	(1.68)	(3.64)
SG	0.851***	0.885***	0.703***	0.761***	0.866***
	(6.36)	(6.53)	(4.63)	(4.74)	(6.47)
SP	0.360**	0.316*	0.254*	0.560***	0.333*
	(2.07)	(1.82)	(1.71)	(2.73)	(1.92)
WP	-0.763***	-0.845***	-0.738**	-0.614*	-0.824***
	(-2.78)	(-2.85)	(-2.47)	(-1.82)	(-2.88)
SGH	0.437***	0.409***	0.312**	0.403***	0.394***
	(3.74)	(3.52)	(2.29)	(2.88)	(3.46)
SGL	-0.414***	-0.476***	-0.391***	-0.358***	-0.472***
	(-4.16)	(-4.23)	(-3.40)	(-2.85)	(-4.29)
SGH*SPH	0.300**	0.229*	0.246	0.291*	0.256**
	(2.35)	(1.80)	(1.61)	(1.93)	(2.08)
SGL*SPL	-0.060	-0.087	-0.008	-0.269*	-0.077
	(-0.47)	(-0.62)	(-0.06)	(-1.81)	(-0.56)
SGH*WPH	-0.491**	-0.591***	-0.347	-0.592**	-0.561***
	(-2.32)	(-2.66)	(-1.43)	(-2.25)	(-2.61)
SGL*WPL	0.272	0.254	0.391**	0.022	0.263
	(1.40)	(1.17)	(1.96)	(0.10)	(1.23)
MV	0.000	-0.000***	-0.000	0.000	-0.000***
	(0.53)	(-2.56)	(-0.05)	(1.20)	(-2.63)
PB	-0.158**	-0.194**	-0.289***	-0.169**	-0.194**
	(-2.19)	(-2.18)	(-3.01)	(-2.39)	(-2.18)
TURN	-0.018***	-0.023***	-0.018***	-0.015***	-0.023***
	(-4.73)	(-5.03)	(-3.41)	(-3.82)	(-5.02)
ILQD	0.131**	0.054***	0.098*	0.272***	0.056***
	(2.21)	(3.68)	(1.65)	(2.76)	(3.74)
BASK	11.160	1.771	26.176	8.709	0.960
	(0.68)	(0.09)	(1.57)	(0.46)	(0.05)

IVOL	-0.059	-0.082	-0.111	-0.112	-0.092
	(-0.61)	(-0.71)	(-1.13)	(-1.10)	(-0.81)
BETA	0.440***	0.177	0.363**	0.430**	0.209
	(2.54)	(0.98)	(2.13)	(2.30)	(1.15)
PR01	0.003	0.006	-0.003	0.004	0.006
	(0.43)	(0.74)	(-0.38)	(0.55)	(0.70)
PR12	-0.060	0.135	0.088	-0.053	0.135
	(-0.20)	(0.46)	(0.26)	(-0.16)	(0.47)
Adj. R^2	11.362	9.530	11.418	12.054	9.537

Table 8. Arbitrage Cost, Investor Attention, and Strongly Persistent Revenue Momentum

For each month t from January 1990 to December 2019, we separate stocks into three portfolios using control variables associated with arbitrage cost and investor attention. Within each control group, we independently sort stocks into three portfolio ranks on the basis of revenue growth (RG) in month $t-1$ (lagged one period) and three portfolio ranks on the basis of RG in month $t-2$ (lagged two periods). Within each control group, the strongly persistent portfolios are constructed from the intersections of the three lagged one-period RG portfolios and three lagged two-period RG portfolios. The strongly persistent portfolios contain stocks with the same lagged one-period and lagged two-period portfolio rank. For example, the portfolio $\text{Low}_{\text{strong}}$ contains stocks with the lowest portfolio rank during months t and $t-1$. The revenue momentum portfolio is constructed by long-buying the stocks with the persistently highest RG ($\text{High}_{\text{strong}}$) and short-selling the stocks with the persistently lowest RG ($\text{Low}_{\text{strong}}$). The spread is the difference (High − Low, H − L) between revenue momentum in the two extreme control portfolios. The portfolios are held for 1 month during month $t+1$ and rebalanced each month, and the portfolio returns are either equally (EW) or value-weighted (VW). The arbitrage cost measures comprise market value (MV), illiquidity (ILQD), relative bid–ask spread (BASK), and idiosyncratic volatility (IVOL). The attention measures comprise nearness to the 52-week high (H52), information discreteness (ID), and the recency ratio (RR). t statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All numbers are percentages.

Panel A: Variables associated with arbitrage costs

	Low MV			High MV			Spread
	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	
VW Raw	0.748	1.889***	1.141***	0.229	0.866*	0.637**	-0.504
	(1.28)	(3.72)	(4.45)	(0.52)	(1.90)	(2.29)	(-1.52)
VW alpha	0.032	1.252***	1.220***	-0.161	0.525***	0.686***	-0.534*
	(0.17)	(8.13)	(4.95)	(-0.88)	(2.80)	(2.56)	(-1.66)
	Low BASK			High BASK			Spread
	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	
VW Raw	0.107	1.133**	1.026***	0.533	1.177***	0.644*	-0.382
	(0.23)	(2.41)	(3.16)	(1.15)	(2.67)	(1.78)	(-0.94)
VW alpha	-0.439*	0.644***	1.083***	-0.056	0.698***	0.754**	-0.329
	(-1.92)	(2.90)	(3.40)	(-0.24)	(3.00)	(2.21)	(-0.81)
	Low ILQD			High ILQD			Spread
	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	
VW Raw	0.177	0.757	0.580*	0.512	2.040***	1.528***	0.948***
	(0.36)	(1.57)	(1.95)	(1.15)	(4.60)	(5.83)	(2.68)
VW alpha	-0.262	0.357*	0.619**	-0.023	1.544***	1.567***	0.948***
	(-1.31)	(1.67)	(2.11)	(-0.13)	(6.90)	(6.03)	(2.68)
	Low IVOL			High IVOL			Spread
	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	$\text{Low}_{\text{strong}}$	$\text{High}_{\text{strong}}$	H-L	
VW Raw	0.065	0.703	0.638**	0.029	1.299**	1.270***	0.632
	(0.15)	(1.64)	(2.22)	(0.05)	(2.44)	(3.56)	(1.61)
VW alpha	-0.350*	0.332*	0.682**	-0.487*	0.863***	1.350***	0.668*
	(-1.72)	(1.74)	(2.45)	(-1.81)	(3.04)	(3.87)	(1.72)

Panel B: Variables associated with investor attention

	Low ID			High ID			Spread
	Low_{strong}	$High_{strong}$	H-L	Low_{strong}	$High_{strong}$	H-L	
VW Raw	0.338	1.288***	0.950***	0.001	0.683	0.682**	-0.268
	(0.65)	(2.61)	(2.56)	(0.00)	(1.53)	(2.41)	(-0.62)
VW alpha	-0.185	0.875***	1.060***	-0.457**	0.267	0.724***	-0.336
	(-0.72)	(3.48)	(2.95)	(-2.30)	(1.37)	(2.66)	(-0.79)
	Low RR			High RR			Spread
	Low_{strong}	$High_{strong}$	H-L	Low_{strong}	$High_{strong}$	H-L	
VW Raw	-0.540	0.267	0.807***	0.521	1.587***	1.066***	0.259
	(-1.15)	(0.58)	(2.84)	(1.08)	(3.16)	(3.31)	(0.61)
VW alpha	-1.040***	-0.193	0.847***	0.108	1.219***	1.111***	0.264
	(-4.74)	(-0.88)	(2.99)	(0.48)	(4.74)	(3.47)	(0.62)
	Low H52			High H52			Spread
	Low_{strong}	$High_{strong}$	H-L	Low_{strong}	$High_{strong}$	H-L	
VW Raw	0.351	1.069*	0.718**	0.187	1.415***	1.228***	0.510
	(0.58)	(1.75)	(2.28)	(0.44)	(3.09)	(4.14)	(1.20)
VW alpha	-0.254	0.490*	0.744**	-0.188	1.090***	1.278***	0.534
	(-0.90)	(1.78)	(2.38)	(-0.88)	(4.94)	(4.46)	(1.62)