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The conservatism bias in an emerging stock market: Evidence from Taiwan $^{\stackrel{\hookrightarrow}{\bowtie}}$

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ABSTRACT

Behavioral theories predict that investors underreact to earnings announcements stemming from the conservatism bias and overreact to a string of earnings news due to representativeness heuristic. This paper thus examines trading strategies of buying past high EPS growth stocks and selling past low EPS growth stocks over 4 to 20 quarters. The results generally support conservative reactions in the medium-term horizon, but provide little support for the over-use of representativeness heuristic on the long-term horizon. Moreover, we find that investors react differently to the consistency sequences of the two extreme earnings growth portfolios.

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1. Introduction

In recent years the finance literature has documented two market anomalies: underreaction and overreaction. Barberis et al. (1998) attribute these two findings to human psychological biases — namely, conservatism and representativeness heuristic — in which investors misreact to a string of news such as earnings announcements. Empirical and experimental evidence unfortunately shows mixed results. Chan et al. (2004) and Durham et al. (2005) provide little support for the parsimonious model of Barberis et al. (1998), while some studies are supportive (e.g. Bloomfield and Hales, 2002; Frieder, 2004). A common feature of these studies is that they all use U.S. market data. In this paper we provide empirical tests using

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¹ For example, Chan et al. (2004) and Frieder (2004) use U.S. securities exchange data. Durham et al. (2005) test college football wagering market data in the United States. Bloomfield and Hales (2002) conduct laboratory experiments with MBA student subjects.

data from the Taiwan Stock Exchange (TSE), uncovering additional insights into the heuristic simplification of investors.

In the model hypothesized by Barberis et al. (1998), investors do not realize that earnings follow a random walk. They misperceive that earnings belong to either a mean-reverting regime (in which investors react slowly to earnings announcements and exhibit conservatism) or a trending regime (in which investors extrapolate past earnings trends and show representativeness). These two behavioral biases accommodate the predictability of momentum and reversal in returns. However, Chan et al. (2004) fail to provide evidence of returns' predictability using U.S. market data. They identify the possibility of considerable arbitrage in the U.S. market, which quickly removes systematic mispricing resulting from investors' information processing biases.

Taiwan's stock market is mainly dominated by domestic individual investors who constituted about 92% of market volume in 1990, but who still made up 71% by 2006. Chui and Wei (1998) find that Taiwan has the largest standard deviation of monthly excess returns among the five Pacific-Basin emerging markets.² Titman and Wei (1999) attribute this high volatility phenomenon probably to the *investor sentiment* story, because of the pervasive low level of sophistication encountered in this market. There is on average about one brokerage account per family,³ and trading costs are extremely low for small investors. This peculiar characteristic in Taiwan's stock market enables us to test the prevalence of investors' behavioral biases.

According to Barberis et al. (1998), the most relevant variables in their model should be the sequences of earnings. We characterize earnings as earnings per share (EPS) due to its salience and availability, whereby what analysts or investors are most concerned about is the improvement or deterioration of EPS.⁴ Consequently, to formalize the sequential arrival of earnings information, we use quarterly EPS data to track the trends and sequences of listed firms' earnings.⁵

Most listed firms in Taiwan have fiscal years ending in December and are required to publish their quarterly financial statements to the market. Thus, investors regularly receive the same monthly extent of accounting performance reports for nearly all listed firms during the same period of time. While the fiscal periods of U.S. companies are clustered in June, September, and December fiscal year-ends (Asthana and Balsam, 2001), the sequences of financial statement releases are non-synchronous in terms of monthly performance measures. In addition, not all countries require listed firms to prepare quarterly financial reports. Taking the United Kingdom as an example, the London Stock Exchange only requires listed companies to submit interim (semiannual) and annual reports. Realizing these environmental differences will help increase our understanding of how earnings sequences have impacts on investors' behavior.

When investors overreact or underreact to the trends and sequences of EPS growth, then implementing trading strategies of buying past high EPS growth stocks and selling past low EPS growth stocks generates either negative or positive results. Thus, we examine different time horizons from 4 to 20 quarters of past EPS growth in conjunction with holding periods ranging from 3 to 12 months. Doing so gives a set of 20 trading strategies.

We find that the raw return behavior is predictable in the medium-term horizon. In other words, there is an underreaction to the high and low growth trends which represents an implication of the conservatism bias. After controlling for the Carhart four-factors, the underreaction still exists in the medium-term horizon. The low growth portfolios are somewhat riskier than high growth portfolios in terms of the market beta, size, and book-to-market factors,

Once investors perceive a firm as extremely high (low) growth, then consistent sequences of EPS growth lead investors to fall into the trending regime, and they overreact. On the other hand, inconsistent sequences of EPS growth lead investors to stay in the mean-reverting regime, and they underreact. The results show an asymmetric reaction in the consistency tests of the two separately high and low growth portfolios. The differences in returns between consistent and inconsistent sequences are insignificant. Few exceptions occur at a 20-quarter horizon which shows return reversals with an implication of

² The five Pacific-Basin emerging markets are Hong Kong, South Korea, Malaysia, Taiwan, and Thailand.

In 1993 the population in Taiwan was 20.9 million and the number of brokerage accounts was 5 million (Titman and Wei, 1999, p. 43). At the end of 2006, the population in Taiwan was approximately 23 million and there were 7.9 million brokerage accounts.
 We are grateful to an anonymous referee for providing this insight.

⁵ The annual earnings numbers are meaningless in this context, as the accumulation of the first quarter to the fourth quarterly financial data comprises a firm's annual data.

representativeness heuristic for the high growth portfolios, and a delayed reaction occurs at a 16-quarter horizon for the low growth portfolios.

This paper tests the trend and sequences using the adjusted EPS to preclude stock dividends and/or stock splits effects since they are very common in Taiwan. The adjusted EPS is calculated as multiplying the EPS with the weighted average number of shares outstanding of the current quarter and then dividing it by the weighted average number of shares outstanding of the preceding quarter.

Overall, our results generally support underreaction stemming from the conservatism bias in the medium-term horizons. However, we find little support for the over-use of reprensentativeness heuristic as described in behavioral theories.

The paper is organized as follows. Section 2 provides some psychological evidence and the link to the operational definitions. Section 3 describes the data. Section 4 presents the empirical results. Section 5 concludes.

2. Psychological evidence and operational definitions

People often resort to heuristics in making a judgment under uncertainty. One such fast and frugal rule of thumb is representativeness, as discussed in Tversky and Kahneman (1974, p. 1125), concerning the misconceptions of chance, in that "people expect that a sequence of events generated by a random process will represent the essential characteristics of that process even when the sequence is short." In financial markets, when investors observe the past streak of a firm's earnings and overreact by its representative to the stereotype of a high (low) growth company, the disappointment after a disconfirming earnings announcement surely predicts subsequent return reversals. On the other hand, Edwards (1968) documents that people are conservative in incorporating the impact of new evidence. Thus, when investors underreact to the trends of past earnings performance, they actually predict future momentum in returns.

Recent finance literature proposes a behavioral explanation for short- and medium-term underreactions and long-term overreaction to corporate performance. For example, Rabin (2002) provides some psychological evidence of the law of small numbers, in which one of the manifestations is the local representativeness bias. Barberis et al. (1998) present a model that allows for a combination of conservatism bias to single shocks of earnings and representativeness heuristic to a streak of earnings numbers.

However, the length of the past financial performance and the time horizon over which the behavioral biases generated are unclear and unspecified in most behavioral models. Barberis and Thaler (2003) posit that there is really only one scientific way to compare alternative theories, behavioral or rational, and that is with empirical tests.

2.1. Relative EPS growth portfolios

According to behavioral theories, investors either overreact or underreact to the different aspects of earnings announcements. Thus, the results for different trading strategies based on past relative EPS growth and several time horizons will be predictable. Investors, due to conservatism bias, update themselves gradually to information contained in the recent earnings announcement. They expect those high EPS growth firms as steadily growing and those low EPS growth firms as steadily falling. Jegadeesh and Titman (1993, 2001) find evidence of momentum in returns which show significant profits at medium-term horizons.

Chan et al. (2004) specify the past four quarters as medium term and find evidence of conservatism bias over such a horizon. One may argue that the sequence of the past four quarters is not sufficient for investors to over-extrapolate extreme earnings growth using the representativeness heuristic. Therefore, the authors also test for a longer time horizon (i.e., 5 years), and find no evidence of reversal in returns stemming from the representativeness bias. In this paper we provide alternative time horizons ranging from 1 year (4-quarter horizon) to 5 years (20-quarter horizon) in order to examine whether different trading strategies generate predictability in returns.

⁶ We are grateful to an anonymous referee that led to this analysis.

Formation Period

Holding Period

(Quarterly EPS announcement)

(4 to 20 quarters)

(3 to 12 months)

Fig. 1. Time line showing sample periods.

To test the predictions of behavioral theories, we consider those portfolios with relative high and low EPS growth over the past J-quarter, and J = 4, 8, 12, 16, or 20 quarters. At the end of each quarter, we compare the EPS with the EPS of the preceding quarter. If the result is higher (lower), then that quarter is classified as a positive (negative) growth in EPS. The stocks are ranked in ascending order on the basis of the sequences of positive or negative EPS growth, and next ranked on the magnitude of EPS. The highest decile is the high growth portfolio and the lowest decile is the low growth portfolio.

To increase the power of our tests, we construct overlapping portfolios in the spirit of Jegadeesh and Titman (1993, 2001). For instance, a 4-quarter high (low) growth portfolio comprises 10% of the stocks with the highest (lowest) EPS growth over the previous quarters Q_{-1} to Q_{-4} , the previous quarters Q_{-2} to Q_{-5} , and so on up to the previous quarters Q_{-4} to Q_{-7} . We hold the portfolios for T months which vary from 3 to 12 months. The formation and holding periods constructed in this paper can be illustrated in the following time line as shown in Fig. 1.

2.2. Consistency growth portfolios

The past earnings trend manifests the relative strength of earnings growth, and investors tend to misperceive firms classified as extremely high or low growth. If the EPS of a high (low) growth firm is consistently above (below) the median of the contemporaneous firms, then this salient information amplifies investors' biased expectations. A firm which has consistently past high (low) growth rates increases the credibility of being a successful (distressed) firm. On the other hand, when a firm shows inconsistent sequences of EPS growth exhibiting a non-trending pattern, investors are unlikely to over-extrapolate existing trends.

A firm with consistent sequences of extreme earnings growth will generate greater return reversals than those firms with inconsistent sequences. In other words, if we buy stocks that have consistent sequences and sell stocks that have inconsistent sequences, hence these trading strategies yield negative abnormal returns with an implication of representativeness bias.

The consistency sequences are extracted from high growth portfolios formed based on past J-quarter that have 4 quarters (for J = 4), 6 quarters (for J = 8), 8 quarters (for J = 12), 10 quarters (for J = 16), and 12 quarters (for J = 20) above the median growth of the entire contemporaneous firms are considered "consistent". The high growth portfolios formed based on past J-quarter that have 1 quarter (for J = 4), 3 quarters (for J = 8), 4 quarters (for J = 12), 5 quarters (for J = 16), and 7 quarters (for J = 20) below the median growth of the entire contemporaneous firms are considered "inconsistent".

The low growth portfolios formed based on past J-quarter that have 4 quarters (for J=4), 6 quarters (for J=8), 8 quarters (for J=12), 10 quarters (for J=16), and 12 quarters (for J=20) below the median growth of the entire contemporaneous firms are considered "consistent". The low growth portfolios formed based on past J-quarter that have 1 quarter (for J=4), 3 quarters (for J=8), 4 quarters (for J=12), 5 quarters (for J=16), and 7 quarters (for J=20) above the median growth of the entire contemporaneous firms are considered "inconsistent".

It is easier to accomplish consistent EPS growth in a shorter period. For example, a firm can maintain the past four quarters of EPS growth above the median growth of the entire contemporaneous firms. When the

⁷ In the construction of portfolio formation, Jegadeesh and Titman (1993) select stocks based on their returns over 1, 2, 3, or 4 quarters, whereas we consider portfolios based on their past EPS growth over 4 to 20 quarters. The major distinction is due to the availability of obtaining quarterly, but not monthly EPS data. Since the sequences of 1 to 3 quarters are too short to form behavioral biases, we follow the length ranging from 4 to 20 quarters as proposed in Chan et al. (2004).

time horizon is longer, the firm shows vicissitudes of EPS growth. Thus, we are unable to find firms with all 20 quarters above (below) the median growth in the contemporaneous period in the 20-quarter horizon for high and low growth portfolios.

Although choosing the number of quarters to define consistency EPS growth is in part under consideration of the sufficiency of observations, we also test alternative number of quarters in which the tenor of the results is similar to the reported results.⁸

2.3. Returns calculations

To evaluate the effect of behavioral biases on return predictability, we employ the Carhart (1997) four-factor model time-series regressions to calculate abnormal returns as follows:

$$R_{\rm pt} - R_{\rm ft} = \alpha + b(R_{\rm mt} - R_{\rm ft}) + sSMB_t + hHML_t + mUMD_t + \varepsilon_{\rm pt}, \tag{1}$$

where $R_{\rm pc}$ is the monthly return on portfolio p; 9 $R_{\rm ft}$ is the risk-free rate at month t; 10 $R_{\rm mt}$ is the monthly return on a value-weighted market index; SMB_t is the difference between the returns on portfolios of small and big stocks; HML_t is the difference between the returns on portfolios of high and low book-to-market stocks; and UMD_t is the difference between the returns on portfolios of high-momentum and low-momentum stocks. Thus, the intercept α is the abnormal return. We compute the standard errors using the estimators proposed by Newey and West (1987) with three lags, since the autocorrelation is negligible beyond the third lag, and we lag one quarter for return calculation to ensure that EPS data are publicly available. 12

As argued by Fama (1998), equal weighting portfolio returns give more weight to small stocks, but value weighting can accurately capture the total wealth effects experienced by investors. Thus, we calculate both equal-weighted and value-weighted returns. The tests using value-weighted returns, though untabulated, do not change the tenor of the results.

3. Data

3.1. Description of the stock market

Academia is attracted to Taiwan's stock market due its peculiar features. Chui and Wei (1998) point out that the Taiwan Stock Exchange (TSE) had the largest trading value among the five Pacific-Basin emerging markets in 1993 (US\$343.32 billion). At the end of 1999, TSE as ranked by its market capitalization was the 12th largest financial market in the world (Barber et al., 2007). Notwithstanding the openness to allow foreign institutional investors to invest directly in the market after 1991, ¹³ the TSE market is still mainly dominated by domestic individual investors.

Table 1 presents the descriptive statistics of the TSE market. The number of listed firms has steadily grown from 163 to 688 during 1988–2006. At the end of 2006, the market capitalization reached US

⁸ We re-examine the tests of Tables 6–9, selecting holding periods of 6-month and 12-month horizons with alternative definitions for consistent and inconsistent sequences. Specifically, the high (low) growth portfolios formed based on past J-quarter that have 3 quarters (for J = 4), 5 quarters (for J = 8), 7 quarters (for J = 12), 9 quarters (for J = 16), and 13 quarters (for J = 20) above (below) the median growth of the entire contemporaneous firms are considered "consistent". The high (low) growth portfolios formed based on past J-quarter that have 2 quarter (for J = 4), 4 quarters (for J = 8), 5 quarters (for J = 12), 6 quarters (for J = 16), and 8 quarters (for J = 20) below (above) the median growth of the entire contemporaneous firms are considered "inconsistent". The results, though unreported, remain qualitatively similar.

⁹ We use monthly returns rather than daily returns to attenuate the impact of the daily price up/down limit of 7% imposed in the TSE market. The returns are calculated based on the local currency of the stock price.

¹⁰ The one-month fixed deposit rates paid by the Bank of Taiwan are used as the proxies of risk-free rates. The data are collected from the AREMOS Economic Statistical Databanks compiled and maintained by the Ministry of Education and National Taiwan University.

¹¹ The procedure to calculate returns on zero-investment factor-mimicking portfolios for size and B/M is similar to Fama and French (1993), and that for one-year momentum in stock returns is closely related to Carhart (1997).

¹² It also follows the conventional measurement of stock returns with one-quarter lag as used in Chan et al. (2004), such that by this lapse of time almost all firms' financial reports are publicly available.

¹³ At that time, foreign institutions had to satisfy certain restrictive requirements and a ceiling investment amount was imposed, which was then gradually relaxed. For more discussion, see Titman and Wei (1999, p.45).

Table 1
Descriptive statistics for the TSE market 1988–2006.

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Profile\Year 1988 1992 1996 2000 2004	ะวดกล
riometreal 2000 1992 1890 2000	2000
Market capitalization (US\$ billion) 120 100 274 248 438	KOA
Warker capitalization (05) onnoin 120 100 274 249	9.7
	400
Market capitalization/GDP (%) 97 47 98 82 126	163
	3233333
Trading value (US\$ billion) 281 247 477 917 592	583
1180115 Value (034 011101)	400000000
Turnover (%) 243 259 177	61/12/25
Turnover.(%) 243 259 177	(31.269)R
Number of listed firms 163 256 382 531 697	680

This table is compiled using data from the Taiwan Stock Exchange Corporation.

Summary statistics of relative EPS growth portfolios.

Quarterly EPS	Mean	Median	25% 0.700	75% 1,446	Average market capitalization
4 High 4 Low	1.273 0.590	0.978 0.250	0.560	1,446 0.073	324.83
8 High	1.140	0.978	0.380	1.461	1658.90
8 Low	0.304	0.253	0.260	0.945	1028.60
12 High	0.874	0.580	0.244	1,140	1578,53 (2) (4) (4) (4)
12 Low	- 0.108	0.010	- 0.260	0.210	434,67, (4.5)
16 High	0.803	0.596	0.282	1.076	1762.30
16 Low	- 0.213	0.100	-0.366	0.060	37930
20 High	0.741	0.587	0.280	0.999	1995.10
20 Low	-0.196	-0.100	-0.390	0.143	417272

This table presents summary statistics of relative EPS growth portfolios. EPS is adjusted to preclude stock dividends and/or stock splits effects, calculated as multiplying the EPS with the weighted average number of shares outstanding of the current quarter and then dividing it by the weighted average number of shares outstanding of the preceding quarter. The EPS growth is calculated by comparing the quarterly EPS with the preceding one. If the result is higher (lower), then that quarter is classified as a positive (negative) growth in EPS. The stocks are ranked in ascending order on the basis of the sequences of positive or negative EPS growth, and next ranked on the magnitude of EPS. The highest decile is the high growth portfolio and the lowest decile is the low growth portfolio. Reported are the mean, median, 25th and 75th percentiles, and the average monthly market capitalizations (in millions of US\$ with an average exchange rate of NT\$30 per US\$1) of the respective portfolios. The sample period for the EPS growth formation is January 1988 to December 2006.

\$594 billion, and the ratio of market capitalization to GDP rose to 163% in comparison with the lowest level of 47% in 1992. The trading value hit a peak in 2000 at US\$917 billion. This fact means that Taiwanese individual investors indeed trade quite a lot. 14

Using data from the Taiwan Economic Journal (TEJ), a counterpart combination of CRSP and COMPUSTAT databases in Taiwan, the sample period for the EPS growth formation is from January 1988 to December 2006. In this sample period the TSE confronted many cyclical bull and bear markets as well as the Asia Financial Crisis in 1997. To be included in our sample, all firms are required to have sufficient quarterly EPS data. Banking, insurance, and securities industries are excluded from the sample due to their special accounting treatment.

3.2. Description of the relative EPS growth

Taiwan's listed firms are required to publish quarterly financial reports. Most of them have the first quarter and third quarter ending on March 31 and September 30, respectively, and they are reviewed by CPAs. In turn, the second quarter (semiannual) and fourth quarter (annual) financial statements end on June 30 and December 31, respectively, and they are audited by CPAs. EPS is both salient and easily available to the market. Investors derive views from trends and sequences of EPS announcements and in some cases form biased expectations.

¹⁴ Individual investors are active traders, which may in part be due to relative low trading costs. Each broker is allowed to set its commission rate at a ceiling of 0.1425% on the value of trading. Capital gains are exempted from being taxed. There is only a transaction tax of 0.3% levied on the sale side.

Table 2 provides summary statistics of relative EPS growth portfolios. We use the adjusted EPS, because stock dividends and/or stock splits are very common in Taiwan. To preclude the diluted effects on the calculation of EPS, we restore the earnings power of a firm based on the weighted average number of shares outstanding before the distribution of stock dividends. In other words, the adjusted EPS is calculated as multiplying the EPS with the weighted average number of shares outstanding of the current quarter and then dividing it by the weighted average number of shares outstanding of the preceding quarter.

The earnings power for high growth portfolios is evidently higher than that of the low growth portfolios. For example, the mean EPS in the 4-quarter horizon for high growth stocks is 1.273, which is higher than that of low growth ones at -0.590. As the time horizon to measure past EPS growth is longer, the earnings power is decreasing. A 20-quarter is long enough to capture the vicissitudes of the business. Thus, the means of the EPS in the 20-quarter horizon are 0.741 and -0.196 for high and low growth portfolios, respectively. The average market capitalization for the high growth stocks is larger than that of the low growth ones. In the 8-quarter horizons, the market size for low growth stocks is close to the high growth stocks but the latter still shows larger market capitalization.

4. Empirical results

Recent work in behavioral finance argues that the predictability of returns on high and low growth portfolios is the evidence of investor sentiment (Barberis et al., 1998). Opponents to this argument posit that the result is a compensation for risk. Thus, we first examine the differences of cumulative raw returns on high and low growth portfolios and then use the Carhart four-factor model time-series regression to display abnormal returns after being risk adjusted.

4.1. Raw returns analysis

Table 3 presents the cumulative raw returns based on a trading strategy of subtracting the low-growth from the high-growth portfolios over a given holding period. These portfolios are formed based on J-quarter EPS growth and held for T months. For the different formation and holding periods, we refer to this as a J-quarter/T-month strategy.

The differences between high and low growth portfolios show significantly positive cumulative raw returns in the medium term (4-quarter to 12-quarter horizons) over the subsequent 3 to 12 months, with a

Table 3Raw returns of relative EPS growth portfolios.

Quarterly EPS	Holding period in months				
	3	6	9	12	
4 High	0.051 (9.66)	0.085 (10.86)	0.117 (11.68)	0.152 (12.44)	
4 Low	0.024 (3.33)	0.056 (5.25)	0.099 (7.74)	0,146 (8.93)	
4 Difference	0.027 (2.98)	0.029 (2.21)	0.018 (1.09)	0.006 (0.27)	
8 High	0.062 (10.42)	0.113 (11.50)	0.157 (11.83)	0,200 (11,94)	
8 Low	0.038 (5.79)	0.074 (7.66)	0.115 (9.08)	0,153 (10,23)	
8 Difference	0.024 (2.62)	0.039 (2.85)	0.042 (2.29)	0.047 (2.09)	
12 High	0.056 (9.05)	0.103 (10.58)	0.146 (11,13)	0.177 (11.58)	
12 Low	0.024 (3.16)	0.053 (4.90)	0.080 (6.14)	0.123 (7.34)	
12 Difference	0.032 (3.33)	0.050 (3,37)	0.066 (3.58)	0.054 (2.41)	
16 High	0.046 (7.16)	0.092 (8.90)	0.135 (9.73)	0:160 (10.08)	
16 Low	0.042 (4.67)	0.083 (6.27)	0.125 (8.05)	0.179 (9,02)	
16 Difference	0.004 (0.38)	0.009 (0.50)	0.010 (0.51)	-0.019 (-0.72	
20 High	0.046 (6.97)	0.096 (9.05)	0,131 (9.36)	0.163 (10.18)	
20 Low	0.058 (5.61)	0.110 (6.30)	0.154 (8.08)	0,215 (7,99)	
20 Difference	-0,012 (-1,00)	-0.014 (-0.68)	-0.023 (-0.99)	-0.052 (-1,66	

This table reports the cumulative raw returns based on a trading strategy of subtracting the low-growth from the high-growth portfolios. The formation of high and low EPS growth portfolios is defined in Table 2. The one-quarter lagged after each quarterly EPS for return calculation is to ensure that earnings are publicly available. The sample period for the EPS growth formation is January 1988 to December 2006. The *t*-statistics are reported in parentheses.

Table 4Abnormal returns of relative EPS growth portfolios.

Quarterly	Holding period in months				
EPS	3344444	6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6	95 9 9 9 9 9	12 m 1 m 1 m 1 m 1 m 1 m 1 m 1 m 1 m 1 m	
4 High	0.022 (2.85)	0,029 (2.38)	0.034 (1.52)	0.037 (1.19)	
4 Low	-0.024 (-2.45)	-0,047 (-3.49)	-0.069 (-3.74)	-0.081 (-3.02)	
4 Difference	0.046 (2.62)	0.076 (3.00)	0.103 (2.54)	0.118 (2,02)	
8 High	0.038 (4.03)	0.072 (3.81)	0.088 (3.14)	0,018 (2,46)	
8 Low	0.006 (0.56)	0,006 (0,40)	-0.010 (-0.58)	-0.051 (-1.80)	
8 Difference	0.032 (1.59)	0.066 (1.95)	0.098 (2.14)	0.069 (2.14)	
12 High	0.017 (1.95)	0.014 (1.16)	0.021 (1.04)	0.012 (0.41)	
12 Low	-0.008 (+1.27)	-0.022 (-1.91)	-0.035 (-2.02)	+0.024 (+1.25)	
12 Difference	0.025 (1.66)	0.036 (1.54)	0.056 (1.49)	0.036 (0.73)	
16 High	0.016 (2.55)	0.016 (1.24)	0.013 (0.61)	0.001 (0.01)	
16 Low	0.001 (0.14)	-0.003 (-0.30)	- 0.016 (- 1.37)	-0.020 (-1.37)	
16 Difference	0.015 (1.17)	0.019 (0.79)	0,029 (0.89)	0.021 (0.46)	
20 High	0.012 (1.16)	0.020 (1.01)	0.012 (0.48)	0.010 (0.31)	
20 Low	-0.008 (-0.88)	=0.012 (=0.96)	-0.019 (-1.50)	÷0.018 (=1.13)	
20 Difference	0.020 (1.08)	0,032 (0.99)	0.031 (0.83)	0.028 (0.57)	

This table reports the cumulative abnormal returns based on a trading strategy of subtracting the low-growth from the high-growth portfolios. The portfolios are formed based on J-quarter adjusted EPS growth and held for T months. The definition for the adjusted EPS can be found in Table 2. The Carhart four-factor model time-series regressions are used to calculate the abnormal returns: $R_{\rm pt} = R_{\rm fl} = \alpha + b(R_{\rm mit} - R_{\rm fl}) + sSMB_{\rm c} + hiHML_{\rm c} + mUMD_{\rm c} + \epsilon_{\rm pt}$, where the intercept α is the abnormal returns; $R_{\rm pt}$ is the monthly return on portfolio p; $R_{\rm fl}$ is one-month fixed deposit rates paid by the Bank of Taiwan as proxies of risk-free rates; $R_{\rm mt}$ is the monthly return on a value-weighted market index; $SMB_{\rm c}$, $HML_{\rm fl}$, and $UMD_{\rm fl}$ are factor-mimicking portfolios for size, $B/M_{\rm fl}$, and momentum for which the procedures to obtain these factors are similarly described in Fama and French (1993) and Carhart (1997), respectively. The sample period for the EPS growth formation is January 1988 to December 2006. Newey-West t-statistics are shown in parentheses.

few exceptions for 9–12 months in the 4-quarter horizon. For example, the 4-quarter/3-month strategy which buys stocks that have high past growth in EPS and sells stocks that have low growth in EPS yields a significant positive cumulative raw return of 2.7% (t-statistic of 2.98). Table 3 also shows significant cumulative raw returns of 2.4% to 4.7% (t-statistics vary from 2.09 to 2.85) in the 8-quarter horizon and 3.2% to 6.6% (t-statistics vary from 2.41 to 3.58) in the 12-quarter horizon. The results are consistent with the evidence of medium-term underreaction with an implication of conservatism bias. However, we do not observe a significant reversal in returns at longer formation periods, such as in the 16-quarter and 20-quarter horizons. The only significant negative cumulative raw return appears in the 20-quarter/12-month strategy that is marginally significant with -5.2% (t-statistic of -1.66).

Table 5Factor sensitivities of relative EPS growth portfolios.

4 High	0.959 (14.39)	0.238 (3.54)	0.037 (0.83)	0,099 (1.51)
4 Low	1.074 (12.29)	0.835 (8.47)	0.389 (3.22)	-0.071 (-0.79)
8 High	1.183 (13.73)	0.250 (3.10)	0.016 (0.15)	0.114 (0.85)
8 Low	1.049 (12.94)	0.628 (7.75)	0,178 (2,41)	-0.040 (-0.42)
12 High	0.948 (16.62)	0,379 (6.22)	0.144 (2.11)	-0.008 (-0.11)
12 Low	1,008 (16,04)	0.820 (9.13)	0.376 (4.21)	-0.038 (-0.68
16 High	0.991 (12.56)	0.448 (4.17)	0.088 (0.91)	0.121 (1.14)
16 Low	1.067 (16.56)	0.611 (7.15)	0.507 (7.82)	-0.148 (-2.31)
20 High	1.084 (10.68)	0.621 (7.40)	0.012 (0.10)	0.206 (0.78)
20 Low	1.159 (14.39)	0.748 (10.35)	0.595 (6.50)	-0.081 (-0.86

This table reports factor sensitivities of Carhart four-factor model time-series regressions in Table 4. The factor sensitivities are from high and low growth portfolios formed based on six months holding horizons. Factor sensitivities are the slope coefficients in the Carhart four-factor model time-series regressions, "Market" is the market factor (monthly return on a value-weighted market index minus the risk-free rate), "SMB" is the size factor (small minus big stocks), "HML" is the book-to-market factor (high minus low book-to-market stocks), and "UMD" is the momentum factor (up minus down stocks). The sample period for the EPS growth formation is January 1988 to December 2006. Newey-West t-statistics are shown in parentheses.

Table 6Abnormal returns of high EPS growth between consistent and inconsistent sequences.

Quarterly	Holding period in months				
EPS		12 1 6 1 6 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	9 (1)	12	
4 Consistent	0.031 (2.65)	0.031 (1.72)	0.048 (1.97)	0.036 (1.03)	
4 Inconsistent	0.008 (0.38)	-0.006 (-0.29)	-0.012 (-0.30)	-0.013 (-0.31)	
4 Difference	0.023 (0.72)	0.037 (0.92)	0.060 (0.93)	0.049 (0.64)	
8 Consistent	0.030 (2.06)	0.059 (1.68)	0.064 (1.18)	0.064 (1.16)	
8 Inconsistent	0.031 (1.83)	0.061 (1.71)	0.105 (1.77)	0.044 (0.79)	
8 Difference	-0.001 (-0.03)	-0.002 (-0.03)	-0.041 (-0.36)	0.020 (0.18)	
12 Consistent	0.028 (1.38)	0,004 (0,15)	0,053 (1.27)	0.034 (0.55)	
12 Inconsistent	-0.020 (-1.19)	-0,043 (-1,25)	=0.087 (-1.96)	-0.111 (-2.37)	
12 Difference	0.048 (1.30)	0.047 (0.75)	0.140 (1.52)	0.145 (1.33)	
16 Consistent	0.017 (0.56)	=0.035 (=1.02)	-0.052 (-1.29)	-0.098 (-2.16)	
16 Inconsistent	0.118 (1.96)	0.053 (0.78)	-0.032 (-0.53)	-0.118 (-1.76)	
16 Difference	-0.101 (-1.11)	-0.088 (-0.85)	-0.020 (-0.20)	0.020 (0.18)	
20 Consistent	0.002 (0.06)	0.007 (0.16)	-0,031 (-0.59)	- 0.005 (- 0.09)	
20 Inconsistent	0.098 (2.41)	0.076 (1.39)	0.092 (1.15)	0.123 (1.57)	
20 Difference	-0,096 (-1.41)	-0.069 (-0.69)	-0.123 (-0.92)	-0.128 (-0.92)	

This table reports the cumulative abnormal returns based on a trading strategy of subtracting inconsistent sequences from consistent sequences of stocks. The consistent and inconsistent sequences are extracted from high adjusted EPS growth portfolios in Table 3. The high growth portfolios formed based on past J-quarter that have 4 quarters (for J = 4), 6 quarters (for J = 8), 8 quarters (for J = 12), 10 quarters (for J = 16), and 12 quarters (for J = 20) above the median growth of the entire contemporaneous firms are considered "consistent". The high growth portfolios formed based on past J-quarter that have 1 quarter (for J = 4), 3 quarters (for J = 8), 4 quarters (for J = 12), 5 quarters (for J = 16), and 7 quarters (for J = 20) below the median growth of the entire contemporaneous firms are considered "inconsistent". The Carhart four-factor model time-series regressions are used to calculate the abnormal returns as defined in Table 4. The sample period for the EPS growth formation is January 1988 to December 2006. Newey-West t-statistics are shown in parentheses.

4.2. Relative EPS growth analysis

If the predictability of trading strategies in Table 3 is simply a compensation for risk, then after controlling for well-known risk factors, the differences in returns for the trading strategies will appear indistinguishable from zero. Table 4 presents the cumulative abnormal returns of subtracting the low-growth from the high-growth portfolios using the Carhart four-factor model. The difference of the four-factor alpha in the 4-quarter horizon increases from 4.6% (*t*-statistic of 2.62) to 11.8% (*t*-statistic of 2.02) over the subsequent 3 to 12 months. In comparison with other medium terms, some four-factor alphas appear as marginally significantly positive in the 8-quarter and 12-quarter horizons. Notably, after controlling for risk factors, we still find profitability in trading strategies based on past EPS growth at medium horizons.

Implementing the trading strategies over longer horizons, we are unable to find significant four-factor alphas in the 16-quarter and 20-quarter horizons. In other words, there is no evidence of long-term mispricing due to representativeness heuristic.

4.3. Factor sensibilities analysis

To see whether risk loadings show differences between high and low growth portfolios, we report the sensitivities to the Carhart four-factors on the *J*-quarter/6-month strategies. Table 5 shows that the market betas for high and low growth portfolios have small discrepancies, but low growth stocks have higher loadings than high growth stocks on the size factors. For example, the size factor loading for the low growth stocks is 0.835 versus 0.238 for the high growth stocks in the 4-quarter horizon. The same results for the book-to-market factor are that the low growth stocks have a loading of 0.595 on the *HML* factor, whereas the high growth stocks have only a loading of 0.012 in the 20-quarter horizon. The results are somewhat consistent with Jegadeesh and Titman's (2001) findings in which the losers are riskier than the winners, because the losers show higher sensitivity to the market beta, size, and book-to-market factors. However, we are unable to find inherent risk patterns for the momentum factor.

Table 7Abnormal returns of low EPS growth between consistent and inconsistent sequences.

Quarterly	Holding period in months				
EPS	97 (1) 3 (1) 10 10 10 10 10 10 10	6	9 10 10 10 10 10 10 10 10 10 10 10 10 10	12 10 12 12 1	
4 Consistent	-0.034 (-2.23)	-0.052 (-2.01)	-0.085 (-3.05)	-0.121 (-3.64)	
4 Inconsistent	0.005 (0.24)	- 0.002 (- 0.05)	-0.012 (-0.27)	0.001 (0.02)	
4 Difference	-0.039 (-1.11)	-0.050 (-0.89)	-0.073 (-1.02)	-0.122 (-1.22)	
8 Consistent	0.018 (0.71)	0.055 (1.26)	0.091 (1.35)	0.064 (1.18)	
8 Inconsistent	0.011 (0.53)	0.004 (0.14)	0.012 (0.24)	0.015 (0.25)	
8 Difference	0.007 (0.15)	0.051 (0.70)	0.079 (0.67)	0.049 (0.43)	
12 Consistent	-0.002 (-0.14)	-0.020 (-1.12)	-0.051 (-1.82)	-0.091 (-2.18)	
12 Inconsistent	0.082 (1.79)	0.084 (1.31)	0.062 (0.65)	0.090 (0.69)	
12 Difference	-0.084 (-1.41)	-0.104 (-1.26)	-0.113 (-0.91)	-0.181 (-1.04)	
16 Consistent	-0.027 (-2.01)	-0.070 (-4.17)	-0.076 (4.48)	-0.112 (-4.18)	
16 Inconsistent	0.057 (1.34)	0.076 (1.27)	0.084 (1.15)	0.045 (0.58)	
16 Difference	0.084 (1.49)	-0.146 (-1.90)	-0.160 (-1.79)	- 0.157 (- 1.50)	
20 Consistent	0.000 (0.02)	0.011 (0.22)	0.079 (1.00)	0.220 (1.12)	
20 Inconsistent	0.001 (0.01)	0.021 (0.31)	0.060 (0.83)	-0.059 (-0.65)	
20 Difference	-0.001 (-0.01)	-0.010 (-0.09)	0.139 (0.92)	0.279 (0.97)	

This table reports the cumulative abnormal returns based on a trading strategy of subtracting inconsistent sequences from consistent sequences of stocks. The consistent and inconsistent sequences are extracted from low adjusted EPS growth portfolios in Table 3. The low growth portfolios formed based on past J-quarter that have 4 quarters (for J = 4), 6 quarters (for J = 8), 8 quarters (for J = 12), 10 quarters (for J = 16), and 12 quarters (for J = 20) below the median growth of the entire contemporaneous firms are considered "consistent". The low growth portfolios formed based on past J-quarter that have 1 quarter (for J = 4), 3 quarters (for J = 8), 4 quarters (for J = 12), 5 quarters (for J = 16), and 7 quarters (for J = 20) above the median growth of the entire contemporaneous firms are considered "inconsistent". The Carhart four-factor model time-series regressions are used to calculate the abnormal returns as defined in Table 4. The sample period for the EPS growth formation is January 1988 to December 2006. Newey-West t-statistics are shown in parentheses.

4.4. Consistency sequences analysis

Do the consistent sequences of earnings growth have the same impact on both extreme portfolios? In other words, once investors misclassify a firm as a high (low) growth in EPS, consistently high (low) growth sequences cause a delayed incorporation of earnings growth into prices at short-term horizons and reinforce investors to use representativeness heuristic in their long-term horizons. On the other side, inconsistent earnings growth sequences lead investors to stay in the mean-reverting regime and generate little reaction to the stock return.

This subsection examines the trading strategies of consistency sequences in the two high and low growth portfolios. If the consistent sequences exhibit significant momentum in returns, then they suggest the evidence of underreaction with an implication of conservatism bias. On the other hand, if the consistent sequences show significant reversal in returns, then they indicate evidence of overreaction due to representativeness bias.

Table 6 examines the consistency sequences of high growth portfolios and shows that there are no significant differences between consistent and inconsistent sequences in the medium-term horizons (4-

Table 8
Differences between high and low growth consistent portfolios returns.

Quarterly	olding period in months	
EPS	6	12
PROPERTY OF THE PROPERTY OF TH	0.083 (1.88) 0.133 (2.56)	0.157 (2.31) 0.000 (0.01)
14.23.24.24.24.24.24.24.24.24.24.24.24.24.24.	012 (0,30)	0.125 (1,20)
4717. \$5.43 4754. Philadelphia	0.035 (0.68) 0.024 (0.42)	0.014 (0.19)
20 Difference	-0.002(0.04) $-0.004(-0.04)$ $-0.110(-0.83)$	-0.225 (-0.87)

This table reports the difference in cumulative abnormal returns based on a trading strategy of subtracting consistent sequences of low growth portfolios in Table 6. The sample period for the EPS growth formation is January 1988 to December 2006. Newey-West r-statistics are shown in parentheses.

 Table 9

 Differences between high and low growth inconsistent portfolios returns.

Quarterly Holding period in months	
	er et et al area Eregelle da assat albumanta et et et
2	9
4 Difference 0.003 (0.08) -0.004 (-0.08)	0.000 (0.00) -0.014 (-0.13)
8 Difference 0.020 (0.53) 0.057 (0.88)	0.029 (0.85) 0.029 (0.25)
12 Difference -0.102 (-1.64) -0.127 (-1.28)	-0.149 (-1.06) -0.201 (-1.13)
16 Différence 0.061 (0.59) -0.023 (-0.18)	-0.116 (-0.88) -0.163 (-1.13)
20 Difference 0.097 (1.06) 0.055 (0.46)	0.152 (1.00) 0.182 (1.08)
20 Dinerence 0.097 (1.06) 0.055 (0.46)	0.152 (1.00)

This table reports the difference in cumulative abnormal returns based on a trading strategy of subtracting inconsistent sequences of low growth portfolios in Table 7 from inconsistent sequences of high growth portfolios in Table 6. The sample period for the EPS growth formation is January 1988 to December 2006. Newey–West t-statistics are shown in parentheses.

quarter to 12-quarter). The 16-quarter horizon, which is ambiguous in terms of medium or long term, begins to show negative differences in implementing it for up to 3–9 months, though it is insignificant. The 20-quarter horizon is fairly representative of a long-term horizon which shows negative differences over the subsequent 3 to 12 months. This suggests that firms with consistent sequences suffer greater reversal in returns at longer horizons, albeit insignificant.

In comparison with Table 6, we examine the consistency sequences of low growth portfolios in Table 7. We find different features to the high growth portfolios in Table 7. For example, the cumulative abnormal return in the consistent sequences of a 4-quarter/3-month strategy is -3.4% (t-statistic of -2.23), which declines to -12.1% (t-statistic of -3.64) in the 4-quarter/12-month strategy. However, these negative differences should be interpreted with caution. The results suggest a slow incorporation of consistently bad news into stock return.

The difference rows in 8-quarter and 12-quarter horizons provide no statistical significance between consistent and inconsistent sequences. However, the subsequent 6 to 12 months in the 16-quarter horizons show marginally significant negative cumulative abnormal returns, and they are caused by declining cumulative abnormal returns in the consistent sequences from -2.7% in the 16-quarter/3-month strategy to -11.2% in the 16-quarter/12-month strategy. Furthermore, we observe a reversal in returns in the difference row at the 20-quarter horizon, though it is insignificant. The evidence suggests that investors react differently to the consistency sequences of the two high-growth and low-growth portfolios.

4.5. Further analysis of consistency sequences

This subsection examines whether high growth or low growth portfolios provide more momentum or reversal in returns to the consistent (inconsistent) sequences. Table 8 presents the cumulative abnormal returns based on a trading strategy of subtracting consistent sequences of low growth portfolios from those of high growth portfolios. In the 4-quarter horizon, the cumulative abnormal returns in the consistent sequences of high growth portfolios outperform those of low growth portfolios, generating significantly positive differences in returns. For example, the 4-quarter/12-month strategy yields 15.7% (*t*-statistic of 2.31). Although the 20-quarter horizon shows negative differences in returns, they are statistically insignificant. The evidence suggests that investors do not consistently over-extrapolate extreme earnings sequences too far into the future.

Firms with inconsistent sequences in EPS growth are likely to stay in the mean-reverting regime. Behavioral theories predict that investors react slowly to earnings announcements and exhibit conservatism bias. Thus, implementing a trading strategy of subtracting inconsistent sequences of low growth portfolios from those of high growth portfolios generates an insignificant abnormal return. The tests in Table 9 confirm this prediction with an exception of -10.2% (t-statistic of -1.64) in the 12-quarter/3-month strategy which is marginally significant.

¹⁵ We also examine the difference in returns between the more consistent long-short strategy and less consistent long-short strategy in Chan et al. (2004, p. 20). The unreported tests affirm that the consistency sequences in EPS growth have little effect on investors' represenstativeness heuristic, and the results are consistent with Chan et al. (2004).

5. Conclusion

Behavioral theories predict that people assess the outcome which reflects the salient features of the process by which it is generated. The announcement of an EPS represents a salient feature of a firm's earnings power in which investors tend to form biased expectations. Thus, this paper provides an empirical test of behavioral theories using data from the Taiwan stock market.

Prior empirical research has found underreaction over the medium term horizon and overreaction over the long term horizon in the stock market. An alternative behavioral view seeks to explain that investors underreact to earnings news stemming from the conservatism bias and overreact to a string of earnings news due to representativeness heuristic. However, the time horizons over which behavioral biases come into play are unspecified. Thus, we construct trading strategies that comprise 4 to 20 quarters for formation periods and 3 to 12 months for holding periods.

The trading strategies that buy past high EPS growth stocks and sell past low EPS growth stocks yield significant cumulative raw returns in the medium-term horizon. After controlling for the Carhart four-factors, the profitability of such trading strategies still exists in the medium-term horizon. In addition, we find that the low growth portfolios are riskier than the high growth portfolios to the three Fama-French factors.

We further examine the trading strategies based on the consistency sequences in the two separate high and low growth portfolios. The evidence shows that there is a reversal in returns for the high growth portfolios in the long-term horizons, though marginally significant over the 3 months. While we still find slow recognition of consistent low growth sequences, this suggests that investors react differently to the consistency sequences of the two extreme earnings growth portfolios.

This paper examines various time horizons in which we can observe when and how behavioral biases arise. Overall, we find some evidence of conservatism bias in the medium-term horizons, but little support for the over-use of representativeness heuristic. The fact that investors react differently to the consistently high growth sequences versus the consistently low growth sequences invites further research.

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