Empirical Study on Conservative and Representative Heuristics of Hong Kong Small Investors Adopting Momentum and Contrarian Trading Strategies

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Abstract: Recently, a new Bayesian approach has been developed to explain some market anomalies. In this paper, we conduct a questionnaire survey to examine whether the theory holds empirically by studying the conservative and representative heuristics by Hong Kong small investors who adopt momentum and/or contrarian trading strategies. In addition, our study provides evidence for the small investors on their time horizon and risk tolerance when facing uncertainty in their investments. Our findings are useful to small investors in their investment decision making and useful to financial advisors in providing service to small investors.

Keywords: conservative and representative heuristics; momentum and contrarian trading strategies.

1. Introduction

The traditional investment decision theory is originally founded by using the valuation bases that come from capitalism and the idea of a free market economy. However, most of the traditional investment theories fail to explain many anomalies in reality. Market excess volatility, overreaction, and underreaction are the most important anomalies discovered in recent decades. Substantial empirical evidences support the existence of related phenomena that have been founded continuously over the last few decades. For example, evidence of excess volatility suggests that some volatilities of the equity market cannot be justified by variation in subsequent dividends; evidence of underreaction supports the phenomenon that over short horizons, security prices underreact to news; and, on the other hand, evidence of overreaction supports the phenomenon that over long horizons, security prices overreact to news. These observations pose a major challenge to traditional finance and economic theory since these market anomalies could imply that the assumption behind the traditional investment theory may not hold true.

Barberis, et al. (1998) are among the first to build a model to explain related anomalies. They show that underreacting in the short run and overreaction in the long run are resulted from the conservatism heuristics and the repressiveness heuristics. Lam, et al. (2010) extend their work and argue that some investors possess conservative and/or representative heuristics that lead them to underweigh recent observations and/or underweigh past observations of earnings shocks to stock prices. Lam, et al. (2012) further generalize their work and adopt their pseudo-Bayesian approach to develop properties to explain some market anomalies, including short-term underreaction, long-term overreaction, and excess volatility, that reflect investors' behavioral biases. Recently, Guo, et al. (2017) extend their work in order to apply in normal situations and financial crises.

It is an interesting area to investigate whether the theory developed by Lam, et al. (2010, 2012), Guo, et al. (2017), and others work well in the empirical analysis. Working along this direction, Fabozzi, et al. (2013) have developed three test statistics and applied the statistics to investigate whether the US equity market exhibits underreaction or overreaction. Nonetheless, as far as we know, there is no study using a questionnaire to check whether the theory holds for individual investors. To bridge the gap in the literature, this paper examines whether the theory developed by Lam, et al. (2010, 2012) and Guo, et al. (2017) and others holds true for small investors in Hong Kong. Small investors refer to individuals who purchase small amounts of securities for themselves. We choose small investors in our study but not institutional investors because as opposed to institutional investors, small investors could be more prone to psychological factors in making decisions (Ackert, et al., 2015). Academics and practitioners agree that some determinants should play an important role in the investment decision for small investors. But how big is this role? Does the role change for different types of investors? To investigate these questions, we collect data from 1,098 respondents via a survey.

The objectives of our study are to analyze the behavioral heuristics used by Hong Kong small investors who adopt momentum and/or contrarian trading strategies and provide evidence for the small investors on their time horizon and risk tolerance when facing uncertainty in their investments. In our analysis, we also examine other factors, including their sentiments and types of investors in the analysis. Using cluster analysis and factor analysis, we find that small investors' behaviors are influenced by their conservative and representative heuristics, risk tolerance and time horizon. Our findings are useful to small investors in their investment decision making because after reading our paper, small investors will know whether they have conservative and/or representative heuristics and they will know momentum and/or contrarian trading strategies better. This will help them to make a better decision in their investment. In addition, the results of investor's behavioral biases and trading strategies are useful for financial advisors to recognize their clients' heuristics and characteristics so that they are able to provide appropriate investment advice and sell appropriate products to their various clients through revenue management. The professionals also help to reduce the investment loss and enhance investment performance of their clients.

This paper is organized as follows. Section 2 reviews the related literature. Section 3 explains the theory and Section 4 presents the data and methods of the present study. The results are reported and discussed in Section 5 and the concluding remarks and discussions are given in Section 6.

2. Literature Review

Given the classic assumption of rationality, theoretically, investors should base their financial decisions upon knowledge, expectations and experience in the financial markets (Cohen and Kudryavtsev, 2012). However, rationality is imperfect in reality (Tversky and Kahneman, 1973, 1974) and it implies that behavioral biases might actually play a major role in investors' decision-making process (Basu, et al., 2008). Studies that try to relate behavioral biases and investment decision could be date back to Slovic (1972). This kind of studies have wide implications for investment strategies (Fong, et al., 2005, 2008; Shanmugasundaram and Balakrishnan, 2010; McAleer, et al., 2016); thus, understanding investors' behavior will be useful in giving investment advice and making decisions. For example, Wang, et al. (2011) suggest that familiarity bias is common among private investors and that it affects the investors' risk perceptions of investment products. In addition, Peterson (2002) draws on the psychology literature to show that anticipation of reward (price appreciation) generates a positive affect (emotion, mood, or attitude), driving increased risk-taking behavior and buy trading. Following the anticipated event or news, there is a resulting reduction in positive affect that produces more risk-averse behavior and drives sell trading.

The earliest paper addressing conservatism was Edwards (1968), who revealed that when investors with conservative behavior attach too little weight to recent information, they then make behavioral mistakes in their decisions. Grether (1980) considered that individuals who exhibit conservative heuristics update their beliefs too slowly in the face of new evidence. On the other hand, Kahneman and Tversky (1972) explored the representativeness heuristic, according to which the probability of an uncertain event is determined by the degree to which the event is similar in essential characteristics to its parent population and reflects the salient features of the process by which it is generated. The model of Barberis, et al. (1998) is one of the most notable models in this direction. Barberis, et al. (1998) show that underreaction in the short run and overreactions in the long run are resulted from the conservatism heuristics and the repressiveness heuristics. Their model assumes that while earning announcements follow a random walk process, investors using conservative and representative heuristics believe that the announcements fall into a trending regime and a mean reverting regime. Barberis, et al. (1998) then deduce that such behavior may lead to both short term underreaction and long term overreaction in the market. On the other hand, Daniel, et al. (1998) argue that the market will experience short-term underreaction and long term overreaction if some investors are overconfident.

Based on Barberis, et al. (1998), Lam, et al. (2010, 2012) have developed a pseudo-Bayesian framework to model investors' conservative and representative heuristics. They assume that the investor knows the correct underlying model but adopt an incorrect approach in the updating process which reflects investors' behavioral biases and contributes to market anomalies. Recently, Guo, et al. (2017) have introduced a new Bayesian approach to explain some market anomalies including excess volatility, short-term underreaction, long-term overreaction, and their magnitude effects during financial crises and subsequent recovery. The Bayesian approach of Lam, et al. (2010, 2012) and Guo, et al. (2017) provides a theoretical background for our survey study on the behaviors of Hong Kong small investors.

3. Theory

Using a cost of capital model (Thompson and Wong, 1991, 1996; Wong and Chan, 2004), the asset is priced at time t as P_t can be represented by

$$P_t = E_t\left\{\frac{N_{t+1}}{1+r} + \frac{N_{t+2}}{(1+r)^2} + \cdots\right\} = \frac{N_t}{r} + \frac{1+r}{r}\left\{\frac{E_t y_{t+1}}{(1+r)^1} + \frac{E_t y_{t+2}}{(1+r)^2} + \cdots\right\}, \quad (1)$$

where r is the discount rate or the investor's anticipated return, E_t is investor's expectation given the information set Φ_t available to the investor at time t. Lam, et al. (2010, 2012) assume that the earning N_t follows a random walk model in which the earnings shock y_t is independent and follows a Gaussian distribution with mean μ and variance σ_y^2 while Guo, et al. (2017) extend the theory by assuming that the earnings announcement N_t follows the random walk model with/without drift to capture the impact of financial crises. They also assume that the representative agents have to estimate the mean μ by employing observed data on the earnings shock $\{y_t\}$ and the agents use a pseudo-Bayesian model to reflect their behavioral biases. Using this model setup, they find that for any $k \geq 1$ the posterior mean $E_t^S y_{t+k}$ and posterior variance σ_t^2 of μ become

$$E_t y_{t+k} = \frac{\omega_t y_1 + \ldots + \omega_1 y_t}{s_t} \text{ and } \sigma_t^2 = \frac{\sigma_y^2}{s_t}, \text{ respectively where } s_t = \sum_{i=1}^{t} \omega_i \quad (2)$$

and the price at time t using the rational expectations pricing model in equation (1) becomes $P_t = \frac{N_t}{r} + \frac{(1+r)}{r^2}\frac{\omega_t y_1 + ... + \omega_1 y_t}{s_t}$ where $N_t = \sum_{i=1}^{t} y_i$. (3)

Brav and Heaton (2002) consider weights given by $\begin{array}{l}\omega_1 = \cdots = \omega_{\frac{t}{2}} = 1, \\ \omega_{\frac{t}{2}+1} = \cdots = \omega_t = 0.\end{array}$ while Lam, et al. (2010, 2012) and Guo, et al. (2017) extend the theory by assuming that investors using both conservative and representative heuristics assign weights as:

$$0 \le \omega_1 < \omega_2 < \cdots < \omega_{n_0} = \omega_{n_0+1} = \cdots = \omega_{m_0} = 1 > \omega_{m_0+1} > \cdots \ge 0. \quad (4)$$

In equation (4), we will get conservatism when set $m_0>0$, and get representativeness when set $n_0<\infty$. Investors will only have conservative heuristics if $n_0=\infty$, and they will only have representative heuristics if $m_0=0$.

Under this model setting, Lam, et al. (2010, 2012) and Guo, et al. (2017) derive the following results:

a) There exist short-term underreaction and long-term overreactions in price when underreaction and/or event approaches are used, and both expected momentum and contrarian profits are positive when the trading period is long enough.
b) The representative (conservative) heuristic contributes to the contrarian (momentum) profit.
c) Overreaction (underreaction) occurs after long (short) periods of good or bad financial performance.

d) The representative (conservative) heuristic has to overpower the conservative (representative) heuristic to obtain a contrarian (momentum) profit to surface.

In this paper, we will conduct a survey to demonstrate whether the above are correct. We will discuss our approach in next section and discuss the result in Section 5.

4. Data and Methods

4.1 Sample data

Our questionnaire is designed to elicit information about demographics and factors affecting investment decision-making of the respondents. This questionnaire consists of four sections: 7 questions on risk tolerance, 10 questions on investment sentiment, 2 questions on time horizon and 5 questions on demographic characteristics. The questionnaire[1] with 19 items is displayed in the appendix, and the demographic characteristics compiled from the last 5 items are presented in Table 1[2].

The first part of the questionnaire focuses on risk tolerance, which reflects the degree of uncertainty that small investors can bear. Risk tolerance is a function of both risk capacity and risk attitude in which risk capacity is the amount of risk that investors is required to withstand in order to reach financial goals (items 2-4 and items 6-7) while risk attitude, on the other hand, is best considered as a chosen response to the perception of uncertainty (items 1 and 5).

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[1] Refer to Chow, et al (2017) for the questionnaire information.

[2] Refer to Chow, et al (2017) for Table 1.

The second part of the questionnaire is designed to ascertain small investors' sentiments. When investors are overconfident about their analysis based on past performance of stocks and underreact to recent information, thus updating their beliefs too slowly in the face of new evidence, they exhibit conservative heuristics (Edwards, 1968; Grether, 1980). If they are overconfident about the recent information on stocks and pay less attention to past information, thus leading to belief revisions that are too dramatic and exhibiting representative heuristics (Tversky and Kahneman, 1971, 1974; Kahneman and Tversky, 1973). The conservative heuristic is found to contribute to the momentum profit, while, on the other hand, the representative heuristic is observed to contribute to the contrarian trading profit (Lam, et al., 2010, 2012; Guo, et al., 2017).

Based on poor long-term past performance of stocks as shown in item 8, if the respondents believe that the stock price will go down in the future, this reveals their conservative heuristic. They are overconfident about past information on stocks and pay less attention to recent information on stocks. They will then sell the stocks and hope to get profit by using a momentum trading strategy that dictates selling when there is a string of bad news. On the other hand, based on poor recent performance of stocks as shown in item 10, if the respondents believe that the stock price will go up in the future, this reveals their representative heuristics. They are overconfident about recent information on stocks and pay less attention to past information on stocks. They will then buy the stocks, and hope to get profit by using contrarian trading strategy that dictates buying when there is a string of bad news.

Nonetheless, based on good long-term past performance of stocks as shown in item 12, if the respondents believe that the stock price will go up in the future, this also reveals their conservative heuristic. They overweigh the past but underweigh recent information. In this situation, small investors will buy the stock, and then hope to get profit by using a momentum trading strategy that dictates buying when there is a string of good news. In addition, based on good recent performance of stocks as shown in item 14, if the respondents believe that the stock price will go down in the future, this reflects their representative heuristics. They overweigh the recent but underweigh the past information. In such cases, small investors will then sell the stock, and hope to get profit by using contrarian trading strategy that dictates selling when there is a string of good news.

Lam, et al. (2010, 2012) and Guo, et al. (2017) have developed a pseudo-Bayesian model of investment sentiment in which weights induced by investors' conservative and representative heuristics are assigned to observations of the earning shocks of stock prices. Such weight assignments provide a quantitative link between some market anomalies and investors' behavioral biases. Based on the model they developed, they conclude that excess market volatility will result from investors' biased heuristics. The representative heuristics, rather than the conservative heuristic, contributes to excess volatility in the market. As described in item 16, based on poor performance in the long-term past (conservative heuristics) and recent poor performance (representative heuristics), if the respondents believe that the stock price will go up in the future, they will buy the stock, and then hope to get profit by using contrarian trading strategy that dictates buying when there is a string of bad news.

The items on time horizon indicate how long the respondents hold their investments. The data on the demographic profiles of the respondents are collected from the items on demographic characteristics. Data in the present study are collected in Hong Kong via a questionnaire survey. The survey is conducted from September 23, 2013 to October 31, 2013. Since the majority of Hong Kong's population is Chinese, the questionnaire is written in Chinese. After a pilot test on nineteen respondents, some amendments such as rewording of some questions to eliminate ambiguity if there is any are made before we distribute the questionnaire. We select respondents by using the snowball sampling method (Biernacki and Waldorf, 1981). The target population contains groups of small investors in the Hong Kong financial markets. We distribute 1,100 questionnaires to groups of undergraduate students who help us to further disseminate the questionnaires to other respondents of their acquaintance. There are 1,098 selected respondents who complete and return the questionnaires, representing a response rate of 99.8 percent.[3] We remove from our analysis the respondents who have not answered all the questions in the questionnaire.

4.2. Methods

4.2.1 Cluster analysis

The cluster analysis (Everitt and Dunn, 1991; Friedman and Meulman, 2004) provides us with an analytical tool through which we can determine not only the order of determinants of the respondents' investment decision, but also their degrees of difference. In our study, before carrying out any further investigation, itis desirable to partition the items into subgroups so that the items in each group would be similar to

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[3] The response rate used in our paper is the number of participants who completely answered and returned the survey divided by the total number of participants who were asked to answer the survey. It is expressed in a percentage. Thus, in our study, the response rate is equal to (1,098/1,100) x 100% = 99.8%.

each other. We, therefore, apply the cluster method (Everitt and Dunn, 1991; Friedman and Meulman, 2004) to complete the task.

The process of clustering begins by finding the closest pair of items according to a particular measure of attributes and combines those items with the nearest distance to form a cluster. The procedure continues on a step at a time, linking pairs of items, pairs of clusters, or an item with a cluster, by a linkage method until all the clusters are merged into a single cluster. This algorithm is known as the hierarchical clustering method (Johnson, 1967). The results of the hierarchical clustering are presented in the form of a dendrogram.

4.2.2. Factor analysis

The purpose of exploratory factor analysis (Thompson, 2004) is to extract common factors in a factor model based on eigenvalues, factor loadings and reliability tests. We adopt Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy to examine if the items are correlated in order to assess the appropriateness of factor analysis. If the KMO measures are above 0.50 (Kaiser, 1974) and Bartlett's test of sphericity is statistically significant for all items in the questionnaire, this would indicate that the items can be explained by the common factor(s). Hence, it is appropriate to proceed to factor analysis. The factors with eigenvalues of greater than 1.0 (Kaiser-Guttman Rule) will be extracted. In addition, Cronbach's coefficient α, is used as a measure of the internal consistency based on the average correlations between different items. Cronbach's α will generally increase when the correlations among the items increase and the value of 0.60 is suggested to be the minimum limit of acceptance (Hair, et al., 2010). Further, the high values of the corrected item-total correlation indicate that the items under study are measuring the homogenous concept and its acceptable benchmark level is set above 0.3 (Nunnally, 1978).

5. Empirical Findings

The demographic profile of the respondents is reported in Table 1. The data are compiled from the items on demographic characteristics of the questionnaire. Among the respondents, 56.3% are male and 43.7% are female. The majority (88.9%) of the respondents are in the 18-55 age group. Regarding the level of education, a majority (56.6%) of them have tertiary education, and 43.4%havesecondary school education or below. Regarding their employment status, 62.8% of the respondents are employed, 13.8% self-employed, 7.7% retired, and 15.7% classified as “others” which include housewives and students. Finally, the respondents’ median monthly income is $14,410. In view of the above demographic profile for the respondents, we believe that the respondents generally represent the sample of small investors in the Hong Kong.

The average-linkage dendrogram in Figure 1[4] is a tree diagram, which gives a visualization of the hierarchical structure of 19 items from sections 1 to 3 of our questionnaires related to the respondents’ investment behaviors. Before linking the items together in the dendrogram, each item is considered to be a single group at the

[4] Refer to Chow, et al (2017) for Figure 1.

first stage. From the second stage to the twelfth stage in the agglomerative procedure, the number of items is reduced. When the final (thirteenth) stage is reached, there is single group linking all 19 items.

Specifically, the 19 items are classified into three groups at the eleventh stage with the names of the items shown as follows:

Group 1: Duration (item 18), Time (item 19)

Group 2: Risk (item 1), Portfolio (item 2), Goal (item 3), Philosophy (item 4), Mind (item 5), Cash (item 6), and MPF (item 7)

Group 3: The other 10 items (items 8-17) relate to subjective expectation on stock performance and behavioral heuristics

Group 1 is related to investors' time horizon. The 7 items in Group 2 represent risk tolerance. The other 10 items in Group 3 (Expectation 1, Heuristic 1, Expectation 2, Heuristic 2, Expectation 3, Heuristic 3, Expectation 4, Heuristic 4, Expectation 5 and Heuristic 5) represent the investors' sentiments as reflected by their expectations on stock performance and behavioral heuristics.

To further identify the underlying dimensions of the items, factor analysis is then applied to the 19 items. The KMO measure gives a value of 0.788 and the Bartlett's test of Sphericity is significant at the 1% level, indicating that the items are correlated with the common factors. Hence, it is appropriate to proceed to employing factor analysis. We use the principal component analysis for estimation. From the results in Table 2[5] and the Scree plot in Figure 2[6], five factors with their eigenvalues larger than 1.0 are extracted, which can explain over 60% of the cumulative proportion of total variance.

As shown in Table 3[7], the five factors (Factors A, B, C, D and E) describe the different characteristics and behaviors of small investors. These are as follows: Factor A reflects the dimension of risk tolerance which is affected by risk capacity (i.e. Risk and Mind) and risk attitude (i.e. Portfolio, Goal, Philosophy, Cash and MPF). Factor B is interpreted as the investor's sentiment of selling momentum or buying contrarian to reflect investors' expectation on stock performance and behavioral heuristics. If the stock has poor past (recent) performance, respondents believe that the stock price will go down (up) in the future and they will sell (buy) the stock, which shows their conservative (representative) heuristics. They, then, hope to get expected profit by using selling momentum (buying contrarian) trading strategy. Likewise, Factor C represents the investor's sentiment of buying momentum or selling contrarian. If the stock has good past (recent) performance, investors believe that the stock price will go up (down) in the future and they will buy (sell) the stock showing their conservative (representative) heuristics. They then hope to get expected profit by adopting a buying momentum (selling contrarian) trading strategy. Further, Factor D represents the investor's sentiment of buying contrarian. If the stock has poor performance in the long-term past as well as more recently, investors believe that the stock price will go

[5] Refer to Chow, et al (2017) for Table 2.

[6] Refer to Chow, et al (2017) for Figure 2.

[7] Refer to Chow, et al (2017) for Table 3.

up in the future and will buy the stock (representative heuristic) in order to get profit by using contrarian trading strategy. In this case, the representative heuristic, rather than the conservative heuristic, contributes to excess volatility in the market as proposed by Lam, et al. (2010, 2012) and Guo, et al. (2017). Finally, Factor E reflects a dimension of the investor's time horizon (i.e. Duration and Time).

Following this, we estimate the corrected item-total correlation statistics and the Cronbach's coefficient α as the test of homogeneity and internal consistency, respectively. The results reported in Table 4[8] show that each factor can indicate a homogenous concept and illustrate internal consistency when the correlation statistics are all over 0.30 and the α values are all over 0.60. Hence, all factors are retained.

From the above results, the behaviors of small investors are affected by risk tolerance, horizon period, as well as conservative and representative heuristics that are resulted by adopting the momentum and contrarian trading strategies.

6. **Conclusion**

This paper examines the behavior of Hong Kong small investors and provides evidence for small investors' on their time horizon and risk tolerance when facing uncertainty in their investment. We also examine other factors including their sentiment types and demographics information in the analysis. Sentiment means that the subjective expectation reflects investors' conservative and representative

[8] Refer to Chow, et al (2017) for Table 4.

heuristics. We find that there are five factors which accounted for satisfactory 60% of the variance are related to the behavior of Hong Kong small investors in their investment. The factors are risk tolerance, the sentiment of selling momentum or buying contrarian, the sentiment of buying momentum or selling contrarian, the sentiment of buying contrarian, and time horizon.

Using cluster analysis and factor analysis, we find that small investors' behaviors are influenced by their conservative and representative heuristics, risk tolerance and time horizon. The evidence can help financial professionals to recognize their clients' heuristics and characteristics so that they are able to provide appropriate investment advice and sell appropriate products to their various clients through revenue management. The professionals also help to reduce the investment loss and enhance investment performance of their clients.

Now we discuss why the traditional financial models cannot be used to explain many anomalies like overreaction and underreaction but can be explained by using the pseudo-Bayesian approach developed by Lam, et al. (2010, 2012), Guo, et al. (2017), and others. It is because by using the pseudo-Bayesian model, weights induced by investors' conservative and representative heuristics are assigned to observations of the earning shocks of stock prices. This could then be used to derive the formula of the stock price at time t to be a function of the weights to observations of the earning shocks of stock prices (see equation (3)). The k-step ahead forecast stock price and its variance are then dependent on investors' conservative and representative heuristics. Thus, when the pseudo-Bayesian model is used and when investors with conservative heuristics dominate the market, more investors believe that the price will depend on the past performance of the companies and do not believe that the recent price change does matter to the future stock price. This belief could then stabilize the future stock price. On the other hand, if investors with representative heuristics dominate the market, more investors believe that the price will depend on the recent price change, for example, price crashes, and the past performance of the companies is not important, then most investors will believe that the stock price is going to crash, then eventually the stock price will crash. Readers may read Chan, et al. (2014), McAleer, et al. (2016), and the references therein for more information. This could then lead to overreaction and underreaction phenomena. Nonetheless, when the traditional asset pricing models are used, then the k-step ahead forecast stock price and its variance are constant, and thus, investors' conservative and representative heuristics have no effect on the future stock prices, and thus, the traditional asset pricing models cannot be used to explain overreaction and underreaction phenomena.

The pseudo-Bayesian approach developed by Lam, et al. (2010, 2012), Guo, et al. (2017), and others can be used to explain many anomalies like overreaction and underreaction, and thus, it is useful for investors in their investment decision making. Nonetheless, if one could incorporate other information, for example, adopting various new risk measures (Wong and Ma, 2008; Bai, et al., 2012, 2013; Leung, et al., 2012; Ma and Wong, 2010; Niu, et al., 2017), portfolio optimization (Bai, et al, 2009), and portfolio diversification (Egozcue and Wong, 2010; Guo and Wong, 2016) into the pseudo-Bayesian model, one should be able to make even better decision on their investment.

We note that in this paper, we focus on investors with conservative or representative heuristics. However, there are many other types of investors with different kinds of behaviors, for example, risk averters (Markowitz, 1952), risk seekers (Wong and Li, 1999; Wong, 2007; Guo and Wong, 2016), and investors with S-shaped and reversed S-shaped utility functions (Levy and Levy, 2002, 2004; Wong and Chan, 2008; Broll, et al., 2010; Egozcue, et al., 2011; Bai, et al., 2011). Extension to the study on other behavioral biases should, therefore, be made in the future.

Last, we note that we only study small investors in Hong Kong in this paper and the respondents in our study are groups of undergraduate students who help us to further disseminate the questionnaires to other respondents of their acquaintance. Extension could include carrying our approach to other respondents, medium and big investors, as well as investors from other countries but in this paper we do not consider to include other respondents, medium and big investors, as well as investors from other countries because different samples may draw similar conclusion but it is also possible to have completely different conclusions (Moslehpour, et al., 2017). Since our paper is the first paper in this area and since our findings support the theory developed by Lam, et al. (2010, 2012), Guo, et al. (2017), and others, our paper could be set as a landmark in this area. We note that similar to most of the case study papers obtaining findings that support newly developed theories in the literature by using only one sample, a limitation of our study is that it is lack of power. Thus, it is common that after one interesting case study paper published, there are many papers extending the work to use different samples to show that the results are not, by chance, confirming the theory. Hence, comparison with any other samples is interesting but we will leave it to further studies by academics from Hong Kong or any other countries to use their samples to compare whether their findings are the same or different from ours.

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