

Do Experts in Financial Magazines Exhibit the Representativeness Heuristic and Herding Recommendation? Evidence from Taiwan

Yih-Wenn Lai¹

¹ Department of Finance, Ling Tung University, Taichung, Taiwan

Correspondence: Yih-Wenn Lai, Department of Finance, Ling Tung University, Taichung, Taiwan

Received: August 13, 2016

Accepted: September 3, 2016

Online Published: September 10, 2016

doi:10.5430/afr.v5n4p49

URL: <http://dx.doi.org/10.5430/afr.v5n4p49>

Abstract

This paper investigates the use of the representativeness heuristic and herding recommendation by experts in Taiwanese investment magazines. We reveal that high-performing experts exhibit less use of representativeness heuristics and more use of herding stock recommendations than poor performers do. Representativeness and herding recommendations increase when sentiments are pessimistic and during bull markets. In general, more representative stocks yield lower abnormal returns and higher return comovement. However, for high-performing experts, recommendations with some degree of representativeness have a higher abnormal return than do recommendations with no representativeness. In addition, stock return comovement caused by herding recommendations catches more market-level news than does stock return comovement that is caused by representativeness.

Keywords: Representativeness heuristic, Herding, Stock recommendation, Expert behavior

1. Introduction

Making informed investment decisions is very important specifically in competitive markets (Riasi, 2015) that offer tons of different investment opportunities to the potential investors. In this article, we document and explain whether experts in investment magazines overweight or underweight information when recommending stocks and how these recommending behaviors affect price formation and stocks perform in the Taiwanese stock market. Representativeness results in investors labeling an investment as good or bad according to its recent performance (Baker & Ricciardi, 2014). Investors buy stocks after prices rise, expecting these increases to continue, and ignore stocks when their prices are below their intrinsic values. People who use the representativeness heuristic to make investment decisions believe that they can see patterns in what is actually a truly random process. Technical traders' extrapolations based on past data are an example of this type of representativeness. When forming posterior beliefs, people using the representativeness heuristic focus on their current information at the expense of their prior knowledge. In the finance market, the representativeness bias typically leads to initial overreaction. Therefore, representativeness predicts subsequent return reversals. Barberis (2013) argues that the representativeness heuristic is largely responsible for the overly optimistic precrisis expectation formation. Luo (2013) reports that representativeness heuristic traders can derive more expected profit from misevaluations (created by noise traders) than rational traders can. Consequently, traders operating under the representativeness heuristic can endure alongside or even drive out rational traders in the long term.

Herding behavior results when experts (i) receive similar information, leading them to take similar actions, or (ii) gain unrelated new information but make the same decisions because their incentive structure encourages imitation (Jegadeesh & Kim, 2010). Unlike representativeness heuristic traders, who think that current and recent information persists, the herding recommendation occurs when experts emphasize current public news and ignore private news. The motivation of representativeness is irrational, whereas the herding recommendation is rational. Both information-driven and non-information-driven herding recommendations are aimed at yielding the superior performance.

Taiwan's stock market is dominated by domestic individual investors (who constituted approximately 60% of investors in July 2014) rather than institutional or foreign investors. The abilities of individual investors to gather and interpret news are poor. These individual investors consult "financial experts" for advice regarding investment decisions. Financial experts play key roles in collecting, processing, and distributing information about firms to investors. These experts issue value-relevant information for end users about corporate data, though there is

widespread evidence that they fail to fully reflect all the available information in their recommendations (see Ertimur, Muslu & Zhang, 2011; Hribar & McNinnis, 2012; Fang & Yasuda, 2014). Such experts who provide information include employees of investment banks, independent research firms, brokerages, and magazines. Unlike security analysts employed by investment banking firms, experts working for magazines do not exhibit incentive to public the bias research pandering their employers' current or potential relationship clients. In addition to offering general investment-related information about capital markets, magazine experts (Note 1) often provide direct-buy stock recommendations based on self-contained research procedures.

Investment experts do not have equal stock-selection abilities. Fang & Yasuda (2014) report that trading according to All-American analysts' buy and sell recommendations earns investors higher risk-adjusted returns than does following the recommendations of other analysts. The cross-sectional differences in experts' recommendations result from varying human capital endowments. Additionally, many experts specialize in specific firms. One of our research questions is whether high-performing experts exhibit fewer adherences to the representativeness heuristic when selecting stocks than low-performing experts do. To analyze how expert characteristics are associated with adherence to the representativeness heuristic when making recommendations, we construct three rules to distinguish the types of experts. The first rule addresses the media appearance frequency; the media exposure of experts adds an advertisement effect to their stock recommendations. The second rule estimates experts' win probabilities, and the third rule calculates their Sharpe ratios. Both the second and third rules measure experts' firm-specific human capital, which evaluates the strength of an expert's ability to produce firm-specific information. In contrast to assessing win probability, the Sharpe ratio measures risk-adjusted performance, which is excess return against risk.

One variable associated with cognitive bias is investor sentiment which reflects optimism or pessimism about stocks in general (Baker, Wurgler, & Yu, 2012). The existence of positive or negative sentiment in the market may affect all participants, including financial experts. Hribar & McNinnis (2012), analyzing the U.S. market, report that when sentiment is positive, analyst forecasts are more optimistic regarding hard-to-value stocks. Our second research question is how sentiment and market condition affect the representativeness heuristic of experts' stock recommendations.

Under the behavioral view of return comovement, representativeness can lead to sample size neglect (i.e., many investors choose to trade only a subset of all available securities). As these investors' risk aversion and sentiment change, they alter their exposure to the securities they hold, thereby inducing a common factor in the returns of these securities. This "habitat" view of comovement predicts that there is a common factor in the returns of the securities that are the primary holdings of a specific subset of investors such as representativeness traders. Xu, Chan, Jiang, & Yi (2013) confirm the positive association between analyst coverage and stock return synchronicity measured by a firm's R^2 in China. They indicate that star analyst coverage reduces stock return synchronicity. Our final research question is whether stocks with increased representativeness exhibit more stock return synchronicity than those with decreased representativeness do.

The rest of this paper is organized as follows. Section 2 discusses related literature and our hypothesis development. Section 3 details the data and variable construction. Section 4 presents our empirical findings. Section 5 provides concluding remarks.

2. Prior Literature and Hypotheses

Three strands of literature relate to our study. The first strand covers cognitive errors made by analysts during the information production process in developed and emerging markets. Loh & Stulz (2011) examine the paradigm shift hypothesis and report that the probability of an influential recommendation is higher for leader and star analysts. The analysts who are likely to make influential recommendations are highly ranked and have a history of being ahead of the crowd. Rangvid, Schmeling, & Schrimpf (2013) report that young and less experienced forecasters as well as forecasters whose pay depends more on performance relative to a benchmark rely on the beliefs of others when forming their own forecast. Therefore, our testable hypotheses are:

H1a. Experts who are more highly skilled at making stock recommendations relied on representativeness less than those who are less skilled do.

H1b. Experts with high media exposure have an advertising effect on their stock recommendations, thus these stocks have a stronger presence in the minds of other experts.

The second strand of literature is a range of heuristics that may be employed by investors in making sentiment-based decisions (Shiller, 2005). Akhtar, Faff, Oliver, & Subrahmanyam (2012) find that a negative market effect occurs upon the release of unfavorable sentiment news; there is no market reaction for the counterpart favorable news.

Notably, this effect seems most likely to occur in salient stocks (Note 2), which is consistent with the availability heuristic. Hoffmann, Post, & Pennings (2013) report that investor perceptions fluctuate significantly during the financial crisis, with risk tolerance and perceptions being less volatile than return expectations. Corredor, Ferrer, & Santamaria (2014) ascertain that the optimism in analyst forecasts stem from both cognitive bias and strategic behavior. Thus, we posit the following:

H2. Experts' behavior when recommending stocks is affected by sentiment and market status.

The comovement in prices reflects comovement in both fundamental values and behavioral views. Regarding the fundamental view of comovement, Xu et al. (2013) measure the positive association between analyst coverage and stock return synchronicity measured by a firm's R^2 in China and confirm that star analyst coverage reduces stock return synchronicity. In contrast with the fundamental view, Barberis and Shleifer (2003) propose a behavioral view of comovement. They argue that to simplify the portfolio allocation process, many investors first group stocks into categories, such as small-cap stocks or automotive industry stocks, and then allocate funds across these various categories. Hillert, Jacobs, & Müller (2014) find that firms reported on the media exhibit, ceteris paribus, substantially stronger momentum. Media coverage can exacerbate investor biases, leading return predictability to be strongest for firms in the public eye. Therefore, we propose the following hypotheses:

H3a. Stocks with higher representativeness have greater stock return synchronicity than those with lower representativeness do.

H3b. Stocks recommended by more experts incorporate more market-wide information (i.e., have greater stock return synchronicity) than less-recommended stocks do.

H3c. Stocks recommended by numerous experts contain more market-level information (i.e., have greater stock return synchronicity) than those with high representativeness do.

3. Research Design

3.1 Sample Selection

We collect stock recommendations and expert-related data from two popular weekly magazines (*Marbo* and *Wealth Invest Weekly*) (Note 3) in Taiwan from January 2011 through July 2015. Stock returns are calculated by total return, which includes dividend and price changes. We use the Taiwan Economic Journal (TEJ) database as the primary source for stock returns and financial data. To calculate expert performance, we identify experts and note the stocks they cover. Following standard practices, we exclude financial firms. Our results contain 26,896 firm-week observations covered by 66 experts. We then calculate expert performance of portfolios grouped weekly according to the stocks recommended on the Friday of the issue week, resulting in 2,291 portfolio-week observations.

3.2 Expert Classification

We use three approaches to categorize experts. The first approach ranks experts according to number of media appearances (Note 4). Experts who make frequent media appearances (in the top third of the group) are considered to have high exposure, and the others are categorized as having low exposure. The high-exposure group comprises 22 experts, and the low-exposure group comprises 44 experts.

The second approach uses the experts' win probability. First, we calculate the equal-weighted excess return (recommended stock's return minus corresponding market return) of the stocks covered by each expert weekly. For example, in the first week, we measure the week return from January 3, 2011 to January 7, 2011 for each expert featured in the aforementioned magazines. We then count how many times each expert outperformed the market return. The experts are ranked according to the value of the number of times they outperformed the market return divided by the number of total recommendations. Experts who rank in the top third are identified as high win probability experts, whereas all others are deemed non-high win probability experts. To avoid a small sample bias, experts with fewer than 10 recommendations are excluded from the high win probability experts. The high win probability expert group contains 10 experts, and the non-high win probability expert group comprises 56 experts.

The third approach calculates the Sharpe ratio of each expert's weekly recommended portfolio, and ranks experts by their weekly Sharpe ratio median during the study period. We divide the Sharpe ratios into high-, median-, and low-Sharpe ratio groups. The literature commonly uses the Sharpe ratio to assess analysts' performance. We begin our analysis by providing evidence regarding whether the various expert groups exhibit, on average, distinct representativeness heuristic and herding recommendations.

3.3 Representativeness Heuristic Measurement

Because of the representativeness heuristic, people tend to select “hot” and past winner stocks. We define a hot stock as a stock that has better technical analysis or the dominant chip index (i.e., high institutional holding and insider holding).

3.4 Technical Index Analysis

According to the moving average (MA) rule, we assess whether experts place too much weight on short-term information and too little weight on long-term information. Let $P_{j,t}$ ($Q_{j,t}$) denote the price (trade volume) of stock j on day t . The L -day MA indicators of stock j on day t are defined as follows:

$$PA_{j,t,L} = \frac{P_{j,t-L+1} + P_{j,t-L+2} + \dots + P_{j,t}}{L} \quad (1)$$

$$QA_{j,t,L} = \frac{Q_{j,t-L+1} + Q_{j,t-L+2} + \dots + Q_{j,t}}{L} \quad (2)$$

Where $PA_{j,t,L}$ ($QA_{j,t,L}$) is the average prices (trade volume) of the past L days. In this paper, 5-, 20- and 60-day MAs are investigated to consider short- and long-term information. We construct two indexes to act as proxies on the better technical side. A recommended stock whose 5-day MA of price is greater than its 20- and 60-day MAs has an **Index 1** of 1; otherwise, its **Index 1** is 0. A recommended stock whose 5-day MA of price is greater than its 20-day MA but less than its 60-day MA has an **Index 1-1** of 1; otherwise its **Index 1-1** is 0. In general, trade volume pushes up the changes of price, meaning that this logic extends to quantities. A recommended stock whose 5-day MA of trade volume is greater than its 20- and 60-day MAs has an **Index 2** of 1; otherwise, its **Index 2** is 0. A recommended stock whose 5-day MA of trade volume is greater than its 20-day MA but less than its 60-day MA has an **Index 2-1** of 1; otherwise, its **Index 2-1** is 0.

3.5 Chip Index Analysis

We construct Indexes 3, 4, and 5 to identify the dominant chip side. If a stock’s net buying and selling by institutional investors (including foreign institutions, securities investment trust companies, and dealers) and margin trading investors during the final week before the magazine’s issue date is larger than 0, then its **Index 3** is 1; otherwise, its **Index 3** is 0. If only the margin trading inventors’ net buying and selling of the stock is larger than 0, then the stock’s **Index 3-1** is 1; otherwise, its **Index 3-1** is 0. A stock whose percentage of institutional trading is greater than the percentage of margin trading has an **Index 4** of 1; otherwise, its **Index 4** is 0. A stock whose proportion of transactions made by foreigner institutional trading is greater than the proportion of transactions made by domestic institutional investors (including securities investment trust companies and dealers) has an **Index 4-1** of 1; otherwise, its **Index 4-1** is 0. A stock whose proportion of transactions made by dealers is greater than the proportion of transactions made by securities investment trust companies has an **Index 4-2** of 1; otherwise, its **Index 4-2** is 0. Margin trading inventors’ net buying and selling is a proxy for the behavior of individual investors. If both the ratio of margin purchase and short sales of a stock are less than 40%, the stock’s **Index 5** is 1; otherwise, its **Index 5** is 0. If either the ratio of margin purchase or short sales is greater than 40%, **Index 5-1** is 1; otherwise, its **Index 5-1** is 0.

3.6 Past Winner Stocks

We construct an index to indicate whether the past excess return of a recommended stock is larger than 0. The past excess return is defined as the last week (month) return of the recommended stock minus the corresponding market return $R_{j,wt} - R_{m,wt}$ ($R_{j,mt} - R_{m,mt}$) before the magazine’s issue date. A stock whose $R_{j,wt} - R_{m,wt}$ and $R_{j,mt} - R_{m,mt}$ are greater than 0 has an **Index 6** of 1; otherwise, its **Index 6** is 0. If $R_{j,wt} - R_{m,wt}$ is greater than 0 and $R_{j,mt} - R_{m,mt}$ is less than 0, then **Index 6-1** is 1; otherwise, **Index 6-1** is 0.

3.7 Herding Recommendation Measurement

We calculate the number of a stock recommended by various expert groups on this week.

3.8 Investor Sentiment Measurement

Previous studies have used various indicators for the measurement of the sentiment variable. Please see Corredor *et al.* (2014) for a detail survey of these indicators. In this paper, we use the Taiwan e-individual investor sentiment index provided by Shih Hsin University. This index uses a weekly Web survey and focuses on individual investors who trade by using the Internet. According to statistics provided by the Taiwan Stock Exchange, Internet trading comprised more than 45% of total trading volume in November 2014.

3.9 Market Status

Gleason, Mathur, & Peterson (2004) report that investor behaviors differ according to market conditions. We further identify bull, consolidation, and bear market periods, and investigate whether and how the effect of the representativeness heuristic varies among the three market conditions. Similar to Chen, Kuo, Huang, & Chen (2014), we use the moving average convergence divergence (MACD) on the daily close price of the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) to identify trends. To determine the MACD line, the 26-day Exponential Moving Average (EMA) is subtracted from the 12-day EMA. A 9-day EMA of the MACD line is plotted with the indicator to act as a signal line and identify turns. The MACD histogram represents the difference between the MACD and its 9-day EMA (i.e., the signal line). If the MACD histograms of previous two weeks (not including the current week) are positive, then the current issue week represents a bull period. A bear period is considered to have occurred when the MACD histograms of previous two weeks are negative. All other situations are considered a consolidation phase. In total, 51, 122, and 55 weeks are considered bull, consolidation, and bear market periods, respectively.

3.10 Abnormal Return Calculated

To examine if there exists abnormal return of stocks due to the interaction between experts' sharp ratio and representativeness heuristic, we further classify stocks into five portfolios of representativeness heuristic weekly according to each stock's representativeness scores.

We employ the complex index RepreID to measure the extent of the representativeness heuristic by summing up those short-run indexes (1-1, 2-1, 3-1, 4-1, 4-2, 5-1, and 6-1). As a result, RepreID ranges from 0 (no representation) to 6 (high representation). We define portfolios Rep1, Rep2, Rep3 and, Rep4 as the sets of stocks with RepreIDs of 0, 1, 2, and 3, respectively. Stocks with RepreIDs of 4, 5, or 6 are part of portfolio Rep5. Finally, we calculate equal- and value-weighted portfolio returns for each portfolio.

We compute the weekly abnormal return of the portfolios as the intercept, α_p . Excess weekly portfolio returns are regressed on the excess market return for the capital asset pricing model (CAPM); on the excess market, size, and book-to-market factors for the Fama–French model; and on the excess market, size, book-to-market, and momentum factors for the Carhart (1997) four-factor model. The portfolios comprise various expert recommendations. The models are as follows:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{RMRF}(R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \quad (3)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{RMRF}(R_{m,t} - R_{f,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_{i,t} \quad (4)$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{RMRF}(R_{m,t} - R_{f,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{MOM}MOM_t + \varepsilon_{i,t} \quad (5)$$

where intercept α_p measures risk-adjusted weekly abnormal portfolio returns; $R_{p,t}$ denotes weekly returns on portfolio p relative to the risk-free rate $R_{f,t}$ which is captured by the current account rate at the Bank of Taiwan; and $R_{m,t}$ denotes the return on the market portfolio which is approximated by the TAIEX. SMB_t , HML_t , and MOM_t correspond to the weekly returns on size, value premium, and momentum portfolios, respectively.

3.11 Measuring R-square and Its Determinates for the Recommended Representativeness

To examine if the comovement of stocks is affected by the representativeness heuristic, we follow Jin & Myers (2006, hereafter JM) to filter our sample. We first exclude stocks that are not traded in their home markets and stocks that are traded for less than 30 weeks during a particular year (Note 5). For each representativeness heuristic group, we estimate the following linear regression monthly to measure how representativeness affects stock return synchronicity:

$$R_{j,k,t} = \alpha_{j,k,t} + \beta_k R_{m,t} + \varepsilon_{j,k,t} \quad (7)$$

where $R_{j,k,t}$ is the representativeness heuristic group k including stock j 's weekly return at time t , and $R_{m,t}$ denotes the TAIEX return. We measure the firm-specific return by using the residual return from Equation (7). We measure representativeness heuristic group synchronicity by its average R^2 for each month. We use equally weighted averages and also averages weighted by each group's total return variance. To circumvent the bounded nature of R^2 within $[0,1]$, we follow Morck, Yeung, and Yu (2000) in using a logistic transformation of R_k^2 :

$$SYNCH_k = \log \left[\frac{R_k^2}{1 - R_k^2} \right] \quad (8)$$

where $SYNCH_k$ is the empirical measure of monthly synchronicity for five representativeness groups. A high $SYNCH$ indicates that the representativeness heuristic groups are highly correlated with the market. R_k^2 is the coefficient of determination from the estimation of Equation (7) for representativeness heuristic group k .

We use the Fama–MacBeth (1973) method and follow Pontiff's (1996) method to correct serial correlation of the month-by-month regression coefficients. The dependent variable is a logistic transformation of equal-weighted (EW) or variance-weighted (VW) R^2 . We hypothesize that stock return synchronicity is affected by the behavioral view (RepID) and fundamental view factors (i.e., the number of recommendations and experts' performance, respectively). Similar to Morck et al. (2000), we adopt the log of the number of stocks recommended in each representativeness group monthly and the average size of stocks (Note 6) as control variables. In addition, we follow JM by using the kurtosis of the residual return as an additional control variable. Representativeness portfolios with high kurtosis (long tails in residual return distributions) have low R^2 because long tails indicate more extreme firm-level news exhibit stock recommendation. Higher amounts of firm-level news appear when representativeness is lower. The explanatory variables are the average skewness of residual returns, average sharp ratio of experts, number of recommendations, RepID, and stock recommended volatility. All the variables are calculated monthly and averaged quarterly.

Similar to JM, we use the skewness of the residual return from Equation (7) to measure the likelihood of extreme firm-level news. Both favorable and unfavorable news relating to firm-specific information is considered, meaning that the occurrence of such news in a particular period reduces R^2 in that period. Because high-performing experts issue stock recommendations for individual companies, it is reasonable to expect that these high performers acquire more firm-specific information than low performers do. Therefore, R^2 should decline for experts with high Sharpe ratios. Many studies also suggest a positive association between analyst coverage and stock return synchronicity. Therefore, an individual stock with increased recommendations is associated with a higher consensus expectation.

Representativeness is accompanied by low-performing experts' recommendations. We hypothesize that a positive relationship exists between representativeness and stock return synchronicity. We then add the portfolio's return volatility into the regressions as an additional independent variable. To ensure that the variables of interest in the regressions are not proxies for differences in portfolio risk, the portfolio's return volatility is measured in terms of the variance of each representativeness group's return.

4. Results

Table 1 provides descriptive statistics for the recommended stocks. In Panel A, the stocks recommended by the high-exposure experts have greater capitalization, increased following compared with the week after the experts' recommendation, more herding recommended behavior in the issue week, and higher domestic institutional and individual investor holdings than those recommended by the low-exposure experts. In Panel B, the stocks recommended by the high win probability experts have higher returns on the issue date and week. These stocks also have lower volatility and beta, more following (herding) recommended behavior in the week after (week of) the recommendation, and fewer dealers, but higher individual and insider investor holdings than those recommended by the non-high win probability experts group. In Panel C, the stocks recommended by the high Sharpe ratio experts have higher returns on the issue date and week, with lower beta, more herding recommended behavior, and lower domestic institutional holdings. Notably, the stocks recommended by the high win probability experts are more likely to be recommended in the next period by the high Sharpe ratio experts. As seen in Panel D, the stocks recommended in the bull phase have higher returns on the issue date and week, greater size, higher volatility and beta, more following recommended behavior in the week after the recommendation, more herding in the week of the recommendation, and higher domestic institutional holdings than the stocks in other two phases.

4.1 Representativeness Heuristic Association with Stocks Recommendation

Table 2 describes the indicators used to measure the representativeness heuristic regarding the selection preferences of the experts. Table 3 depicts the impact of the representativeness heuristic on stock recommendations. We use a t test on the equality of means for indicators among the three expert classifications (Note 7). The experts with a high Sharpe ratio prefer **Indexes 1** and **6**, whereas experts with a low Sharpe ratio prefer **Indexes 1-1** and **6-1**. This implies that high-performing experts focus more on long-term indicators and use the representativeness heuristic less than low performers do. The indicators of quantity are nonsignificant. According to **Index 4s**, the experts with a low Sharpe ratio prefer to follow international chips, then dealers' chips and investment trusts' chips, in contrast to the other two groups. For **Index 5**, the experts with a high Sharpe ratio (high win probability) prefer **Index 5**, whereas

the experts with a low Sharpe ratio (non-high win probability) prefer **Index 5-1**. This implies that high-performing experts focus more on whether an individual chip is overheating.

4.2 Effect of Sentiment and Market Status on Stock Recommendations and Representativeness

Because sentiment and market status directly affect how experts collect, process, and interpret information, in this section we use a *t* test to detect the impact of sentiment and market status on the herding recommendation and representativeness bias among the three types of expert classification. Table 4 presents the results. In Panel A, all the expert groups except the non-high win probability and low Sharpe ratio groups, have increased herding recommendations when sentiment is pessimistic. All the expert groups tend toward increased herding recommendations during a bull market. No matter the sentiment and market status, all the high-exposure experts, the high win probability, and the high Sharpe ratio experts have significantly more herding recommendations than the other groups do. In Panel B, all the expert groups except the low-exposure and median Sharpe ratio groups display significantly higher representativeness bias when the sentiment is negative. In addition, the high win probability experts (high Sharpe ratio experts) exhibit less representativeness bias than the non-high win probability (low Sharpe ratio) experts do. Regarding market conditions, the representativeness bias of the high win probability and high Sharpe ratio experts exhibit indifference under a bull–bear market.

4.3 Representativeness Heuristic and Abnormal Return

In this subsection, we examine the percentage of the weekly mean abnormal return of five representativeness heuristic portfolios (REP1, REP2, REP3, REP4, and REP5) according to Sharpe ratio. Table 5 presents the results of Equations (3)–(5). Panels A, B, and C report the representativeness heuristic for different performance experts. The portfolios with higher representativeness have significantly negative abnormal returns for all expert types. The REP2 portfolios for the high Sharpe ratio experts have the greatest weekly abnormal returns: 0.416% from CAPM, 0.425% from Fama–French, and 0.388% from the Carhart model. These percentages imply that when excellent experts recommend stocks, they can use a heuristic strategically. However, regarding experts from the other two groups, the REP5 portfolios exhibit the greatest negative and significant abnormal return, demonstrating that the most favorable strategy is less representativeness in stock recommendations.

Table 1. Descriptive statistics of stocks recommended.

		Stock's return	Market capitalization (%)	Std	Beta	# of recom. of high exposure experts in last week	# of recom. of high win prob. experts in last week	# of recom. in this week	Excess return	Foreigner	Investment trust	Dealer	Individual	Insider
Panel A The high-low exposure expert groups														
High exposure experts	Mean	0.267	0.490	5.220	1.073	0.58	0.15	1.66	0.467	12.091	2.79	2.381	23.411	21.761
	Median	0.000	0.131	4.507	1.052	0.00	0.00	1.00	-0.073	5.080	0.43	1.530	22.340	17.180
	Std.	5.860	1.171	3.540	1.126	0.968	0.415	0.970	5.471	15.516	4.712	2.993	17.947	15.934
N=25,721														
Low exposure experts	Mean	0.522	0.395	5.099	1.052	0.30	0.08	1.43	0.652	11.923	2.35	2.378	19.705	21.175
	Median	0.270	0.103	4.397	0.993	0.00	0.00	1.00	0.105	4.660	0.02	1.235	15.720	17.145
	Std.	5.486	1.092	3.396	1.043	0.683	0.296	0.806	5.291	15.853	4.255	3.309	17.598	15.061
N=1,175														
	T-test	0.103	0.000	0.149	0.257	0.000	0.000	0.000	0.400	0.236	0.000	0.022	0.000	0.417
Panel B The high, non-high win probability expert groups														
High win probability experts	Mean	0.598	0.533	5.097	1.054	0.61	0.19	1.78	0.714	12.381	2.81	2.236	24.120	22.052
	Median	0.149	0.126	4.373	1.020	0.00	0.00	1.00	0.033	4.990	0.42	1.360	23.510	17.490
	Std.	5.942	1.333	3.534	1.121	1.005	0.471	1.026	5.522	16.106	4.747	2.974	17.954	15.981
N=6,313														
Non-high win probability experts	Mean	0.180	0.472	5.251	1.077	0.56	0.13	1.61	0.402	11.993	2.76	2.425	22.983	21.638
	Median	0.000	0.131	4.541	1.060	0.00	0.00	1.00	-0.100	5.080	0.40	1.570	21.500	17.100
	Std.	5.811	1.112	3.534	1.123	0.945	0.389	0.941	5.443	15.349	4.677	3.016	17.938	15.870
N=20,583														
	T-test	0.000	0.485	0.000	0.000	0.011	0.000	0.000	0.001	0.998	0.699	0.000	0.000	0.081
Panel C The high, median, and low sharp ratio expert groups														
High sharp ratio experts	Mean	0.558	0.500	5.031	1.023	0.58	0.18	1.76	0.600	11.650	2.73	2.203	24.547	21.955
	Median	0.222	0.116	4.341	1.020	0.00	0.00	1.00	-0.009	4.570	0.26	1.270	24.100	17.190
	Std.	5.736	1.273	3.591	0.976	0.992	0.454	1.027	5.362	15.643	4.700	2.968	17.873	16.004
N=8,653														
Median sharp ratio experts	Mean	0.295	0.472	5.449	1.099	0.54	0.12	1.60	0.540	11.603	2.73	2.444	21.064	22.535
	Median	0.000	0.130	4.692	1.061	0.00	0.00	1.00	-0.084	4.730	0.34	1.490	18.210	18.310
	Std.	6.060	1.096	3.679	1.313	0.922	0.375	0.932	5.831	15.193	4.720	3.113	18.071	16.163
N=13,123														
Low sharp ratio experts	Mean	-0.242	0.500	4.928	1.085	0.64	0.14	1.59	0.098	14.042	2.94	2.527	26.713	19.281
	Median	-0.300	0.163	4.371	1.069	0.00	0.00	1.00	-0.111	7.295	0.80	1.910	26.960	14.690
	Std.	5.411	1.163	2.975	0.765	0.994	0.420	0.920	4.556	16.032	4.616	2.776	16.984	14.731
N=5,120														
	T-test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000
Panel D Market Status														
Bull	Mean	0.683	0.530	5.297	1.173	0.59	0.18	1.72	0.735	11.934	2.89	2.425	22.783	21.839
	Median	0.149	0.140	4.565	1.131	0.00	0.00	1.00	0.033	4.940	0.58	1.560	21.490	17.160
	Std.	6.447	1.301	3.286	1.061	0.987	0.467	1.022	5.881	15.415	4.709	2.966	17.892	16.210
N=8,653														
Consolidate	Mean	0.085	0.464	5.241	1.057	0.58	0.14	1.62	0.494	12.159	2.72	2.416	22.886	21.955
	Median	-0.183	0.128	4.521	1.036	0.00	0.00	1.00	-0.044	5.160	0.38	1.550	21.170	17.540
	Std.	5.559	1.074	3.649	1.202	0.972	0.400	0.945	5.335	15.532	4.640	3.034	17.950	15.963
N=13,153														
Bear	Mean	0.354	0.489	5.093	0.994	0.52	0.12	1.61	0.175	12.300	2.78	2.255	24.193	21.132
	Median	0.421	0.121	4.411	0.991	0.00	0.00	1.00	-0.183	5.080	0.30	1.410	23.540	16.840
	Std.	5.755	1.223	3.568	0.928	0.900	0.367	0.920	5.241	15.799	4.806	2.992	17.930	15.418
N=5,090														
	T-test	0.000	0.001	0.001	0.000	0.002	0.000	0.000	0.001	0.030	0.006	0.001	0.000	0.018
Total	Mean	0.299	0.487	5.219	1.071	0.57	0.14	1.65	0.478	12.136	2.78	2.380	23.174	21.729
	Median	0.000	0.130	4.507	1.048	0.00	0.00	1.00	-0.064	5.090	0.41	1.520	21.950	17.160
	Std.	5.845	1.171	3.543	1.108	0.959	0.411	0.960	5.458	15.567	4.698	3.008	17.939	15.900
N=26,896														

The sample consists of 26,896 firm-expert weeks during 2011 January-2015 July. We exclude financial firms. We classify stocks into three types of expert recommendations. Panel A presents experts grouped by their total number of appearance during our study period. Panel B presents experts grouped by their win probability. Panel C presents experts grouped by their median of weekly sharp ratios during our study period. Panel D presents different market status proxy by the phase of last two weeks before current magazine issued. This table presents these stocks' characteristic including return, the proportion of market capitalization, volatility, beta, the number of last week recommendation by the high exposure expert group, the number of last week recommendation by the high win probability expert group, the number of all experts' recommendation in this week, the excess return ($r_t - r_{m,t}$) of this recommended week, the institutional ownership by foreigners, investment trust, as well as dealer, individual investor and insider holdings. Then the data were analyzed by T-test as statistics method to examine the equality test.

Table 2. List of the indicators to measure selecting preference by experts

Indicator	Descriptive
Index 1	Stock's price with 5-day MAs is greater than 20- and 60-day MAs in last week
Index 1-1	Stock's price with 5-day MAs is only greater than 20-day MAs but less than 60-day MAs in last week
Index 2	Stock's trade volume with 5-day MAs is greater than 20- and 60-day MAs in last week
Index 2-1	Stock's trade volume with 5-day MAs is only greater than 20-day MAs but less than 60-day MAs in last week
Index 3	Institutional inventors' (including foreign institutions, securities investment trust companies and dealers) plus individual inventors' net buy-and-sell is more than 0 in last week
Index 3-1	Margin trading inventors' net buy-and-sell is more than 0 in last week
Index 4	If the percentage of institutional trading is greater than the percentage of margin trading in last week
Index 4-1	If the proportion of transactions made by foreigner institutional trading is greater than the proportion of transactions made by domestic institutional investors (including securities investment trust companies and dealers) in last week
Index 4-2	If the proportion of transactions made by dealers is greater than the proportion of transactions made by securities investment trust companies in last week
Index 5	Both the ratio of margin purchase and short sales are less than 40% in last week
Index 5-1	Either the ratio of margin purchase or short sales is more than 40% in last week
Index 6	Stock's last week (month) return minus corresponding market return $R_{j,wt} - R_{m,wt}$ ($R_{j,mt} - R_{m,mt}$) are both greater than 0 in last week
Index 6-1	Only $R_{j,wt} - R_{m,wt}$ is greater than 0 but $R_{j,mt} - R_{m,mt}$ is less than 0 in last week
RepreID	RepreID sums up those short-run indexes (Index 1-1, Index 2-1, Index 3-1, Index 4-1, Index 4-2, Index 5-1, Index6-1) whenever whose long-run indexes (Index 1, Index 2, Index 3, Index 4, Index 5, Index6) is zero. RepreID value ranges from zero (no representation) to six (high representation).

Table 3. Test of equality in mean selection indicators in stock recommendation

	LEE (A)	HEE (B)	Diff. (A)-(B)	NWPE (C)	HWPE (D)	Diff. (C)-(D)	HSRE (E)	MSRE (F)	LSRE (G)	Diff. (E)-(G)
Index1	0.40	0.39	0.016	0.39	0.39	0.001	0.41	0.40	0.33	0.080***
Index1-1	0.04	0.06	-0.020***	0.06	0.06	0.004	0.06	0.05	0.08	-0.023***
Index2	0.19	0.20	-0.010	0.20	0.20	0.000	0.21	0.19	0.20	0.013
Index2-1	0.03	0.04	-0.009	0.04	0.04	0.000	0.04	0.04	0.05	-0.006
Index3	0.47	0.53	-0.055***	0.52	0.53	-0.011	0.53	0.52	0.52	0.016
Index3-1	0.42	0.43	-0.002	0.43	0.42	0.004	0.43	0.42	0.44	-0.010
Index4	0.45	0.42	0.035**	0.42	0.40	0.028***	0.38	0.45	0.40	-0.017
Index4-1	0.66	0.65	0.012	0.65	0.65	0.003	0.64	0.64	0.68	-0.038***
Index4-2	0.47	0.49	-0.020	0.49	0.45	0.041***	0.46	0.49	0.52	-0.067***
Index5	0.87	0.90	-0.024**	0.89	0.91	-0.017***	0.90	0.90	0.87	0.031***
Index5-1	0.13	0.10	0.024**	0.11	0.09	0.017***	0.10	0.10	0.13	-0.031***
Index6	0.50	0.53	-0.038**	0.53	0.53	0.005	0.55	0.54	0.49	0.055***
Index6-1	0.13	0.10	0.023**	0.11	0.10	0.004	0.10	0.10	0.12	-0.023***
N	1,174	25,722		20,580	6,316		8,653	13,124	5,119	

This table reports tests of equality in means of the indicators for different experts group. These indicators are calculated according the last week market statistics before the issued date. Tests for equality in means between indicators are reported for three expert's classification. HEE denotes the high exposure expert group, LEE denotes the low exposure expert group, HWPE is the high win probability expert group, NWPE is the non-high win probability expert group, HSRE is the high sharp ratio expert group, MSRE is the median sharp ratio expert group, and LSRE is the low sharp ratio expert group. We use T-test and One-way ANOVA test with Scheffe Test. *** indicate significance at the 1% level, ** indicate significance at the 5% level, and * indicate significance at the 10% level.

Table 4. Test of equality in herding recommendation and representativeness bias under different sentiment and market status

	LEE (A)	HEE (B)	Diff.(A)-(B)	NWPE (C)	HWPE (D)	Diff.(C)-(D)	HSRE (E)	MSRE (F)	LSRE (G)	Diff.(E)-(G)
Panel A # of this week recom										
$Seti_{i,t} \geq 0$	1.35(459)	1.65(10,469)	-0.298***	1.60(8,316)	1.76(2,611)	-0.160***	1.74(3,528)	1.59(5,278)	1.58(2,119)	0.158***
$Seti_{i,t} < 0$	1.49(629)	1.68(12,505)	-0.186***	1.62(9,992)	1.81(3,143)	-0.186***	1.79(4,218)	1.62(6,330)	1.58(2,565)	0.207***
Diff	-0.140***	-0.027*		-0.025	-0.050*		-0.050*	-0.032*	-0.001	
Bull	1.56(314)	1.73(6,371)	-0.173***	1.67(5,078)	1.88(1,608)	-0.213***	1.82(2,124)	1.68(3,358)	1.67(1,188)	0.148***
Consolidate	1.41(606)	1.63(12,958)	-0.223***	1.58(10,596)	1.78(2,968)	-0.201***	1.77(4,182)	1.56(6,863)	1.55(2,505)	0.222***
Bear	1.30(245)	1.62(6,146)	-0.324***	1.59(4,689)	1.68(1,703)	-0.086***	1.67(2,246)	1.59(2,801)	1.55(1,342)	0.116***
ANOVA F	5.930***	20.620***		13.837***	13.876***		10.251***	13.959***	6.537***	
Panel B RepreID										
$Seti_{i,t} \geq 0$	1.01	1.07	-0.062	1.08	1.01	0.075***	1.03	1.04	1.18	-0.147***
$Seti_{i,t} < 0$	1.11	1.11	0.003	1.12	1.08	0.043*	1.11	1.05	1.27	-0.166**
Diff	-0.102	-0.043***		-0.038**	-0.070**		-0.071***	-0.011	-0.090**	
Bull	1.18	1.07	0.105	1.09	1.06	0.026	1.06	1.04	1.23	-0.176***
Consolidate	0.97	1.08	-0.113**	1.08	1.05	0.032	1.08	1.01	1.24	-0.161***
Bear	1.11	1.04	0.073	1.06	0.98	0.079***	1.01	1.02	1.13	-0.121***
ANOVA F	3.754**	2.381*		0.477	2.095		2.286	0.454	3.428**	

Tests for equality in means between herding recommendation and representativeness bias are reported for three expert's classification. HEE denotes the high exposure expert group, LEE denotes the low exposure expert group, HWPE is the high win probability expert group, NWPE is the non-high win probability expert group, HSRE is the high sharp ratio expert group, MSRE is the median sharp ratio expert group, and LSRE is the low sharp ratio expert group. $Seti_{i,t} \geq 0$ means the change of sentiment is positive, and $Seti_{i,t} < 0$ means the change of sentiment is negative during last week before the issued date. We use T-test and One-way ANOVA test. The observations are reported in parentheses. The *** indicate significance at the 1% level, ** indicate significance at the 5% level, and * indicate significance at the 10% level.

Table 5. Alphas and betas of representativeness heuristic portfolios

	REP1	REP2	REP3	REP4	REP5	REP1	REP2	REP3	REP4	REP5
Panel A the high sharp ratio expert group					Panel B the median sharp ratio expert group					
Intercept	0.302*** (2.704)	0.416** (3.149)	0.0187 (0.140)	-0.055 (-0.328)	-0.614 (-1.472)	0.105 (0.8405)	0.112 (0.828)	0.199 (1.218)	0.009 (0.051)	-1.066*** (-3.325)
$\hat{\beta}_{RMRF}$	0.901*** (10.893)	1.057*** (13.046)	1.134*** (16.655)	1.217*** (12.550)	1.381*** (6.518)	1.002*** (14.911)	1.025*** (17.411)	1.149*** (18.479)	1.118*** (12.938)	1.342*** (6.063)
Intercept	0.319*** (2.894)	0.425*** (3.3027)	0.016 (0.122)	0.014 (0.082)	-0.655 (-1.524)	0.089 (0.720)	0.103 (0.762)	0.179 (1.118)	0.028 (0.163)	-1.154*** (-3.543)
β_{RMRF}	0.968*** (10.327)	1.112*** (13.767)	1.240*** (17.197)	1.237*** (11.726)	1.457*** (7.382)	1.079*** (15.896)	1.107*** (16.487)	1.244*** (20.175)	1.231*** (14.047)	1.421*** (5.994)
β_{SMB}	0.538*** (3.862)	0.392*** (2.705)	0.634*** (4.349)	0.632*** (3.489)	0.979*** (3.023)	0.474*** (3.997)	0.522*** (4.188)	0.737*** (5.668)	0.684*** (3.984)	0.427 (1.213)
β_{HML}	-0.082 (-0.349)	-0.115 (-0.628)	-0.181 (-1.005)	0.388 (1.187)	0.508 (0.591)	-0.293** (-1.969)	0.015 (0.074)	-0.021 (-0.105)	0.008 (0.035)	0.988*** (2.853)
Intercept	0.247** (1.998)	0.388*** (2.615)	0.056 (0.402)	0.077 (0.446)	-0.660 (-1.479)	0.020 (0.141)	0.001 (0.004)	0.128 (0.780)	0.057 (0.320)	-1.062*** (-2.977)
β_{RMRF}	1.055*** (8.629)	1.170*** (10.163)	1.190*** (13.408)	1.100*** (6.183)	1.475*** (6.456)	1.148*** (14.131)	1.211*** (17.353)	1.303*** (17.076)	1.188*** (9.864)	1.340*** (5.166)
β_{SMB}	0.643*** (4.167)	0.465*** (3.113)	0.547*** (2.938)	0.449* (1.674)	1.010*** (3.509)	0.550*** (4.282)	0.643*** (5.220)	0.807*** (5.751)	0.642*** (2.966)	0.350 (0.964)
β_{HML}	0.136 (0.591)	0.031 (0.121)	-0.349 (-1.338)	0.082 (0.185)	0.558 (0.578)	-0.110 (-0.673)	0.307 (1.391)	0.131 (0.557)	-0.100 (-0.327)	0.802* (1.779)
β_{MOM}	0.253* (1.912)	0.167 (1.007)	-0.179 (-1.084)	-0.349 (-1.210)	0.064 (0.150)	0.228* (1.901)	0.348*** (3.499)	0.184 (1.312)	-0.120 (-0.532)	-0.252 (-0.604)
Panel C the low sharp ratio expert group										
Intercept	-0.172 (-1.424)	-0.144 (-1.247)	-0.492*** (-3.030)	-0.103 (-0.511)	-1.142*** (-2.973)					
β_{RMRF}	0.985*** (10.206)	1.035*** (12.986)	1.105*** (11.650)	1.365*** (17.772)	1.147*** (12.442)					
Intercept	-0.173 (-1.457)	-0.132 (-1.138)	-0.380*** (-2.818)	-0.068 (-0.329)	-1.149*** (-2.977)					
β_{RMRF}	0.963*** (11.737)	1.084*** (16.570)	1.219*** (12.819)	1.396*** (17.026)	1.492*** (10.503)					
β_{SMB}	-0.131 (-0.714)	0.273** (2.344)	0.853*** (5.551)	0.615*** (3.862)	1.086*** (3.672)					
β_{HML}	-0.041 (-0.255)	-0.077 (-0.411)	-0.220 (-1.118)	0.583** (2.278)	-0.046 (-0.170)					
Intercept	-0.288** (-2.195)	-0.132 (-1.045)	-0.302** (-2.003)	-0.008 (-0.044)	-0.782* (-1.9132)					
β_{RMRF}	1.068*** (10.099)	1.084*** (15.085)	1.121*** (9.249)	1.298*** (13.167)	1.286*** (7.914)					
β_{SMB}	-0.010 (-0.058)	0.274** (2.086)	0.690*** (2.885)	0.439** (2.275)	0.574* (1.809)					
β_{HML}	0.272 (1.332)	-0.077 (-0.344)	-0.492* (-1.790)	0.325 (1.126)	-0.741* (-1.904)					
β_{MOM}	0.384*** (2.784)	0.001 (0.007)	-0.329 (-1.626)	-0.301 (-1.636)	-1.094*** (-3.628)					

This table shows the percentage weekly mean abnormal return of the portfolios constructed using the five representativeness classifications under three experts' groups. In order to compute the weekly abnormal return of the portfolios, excess weekly portfolio returns are regressed on the excess market return for the CAPM, on the excess market, size, and book-to-market factors for the Fama-French model, and on the excess market, size, book-to-market, and momentum factors for the four-factor model, respectively. Excess market return, size, book-to-market, and momentum factors are from TEJ database. The abnormal return in each week is the intercept from our regressions. The observations of Rep1, Rep2, Rep3, Rep4, and Rep5 are 7,245; 6,295; 4,169; 1,766, and 539, respectively. The t -statistics calculated use the Newey-West (1987) robust standard errors. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels respectively.

4.4 Explaining Differences in the Representativeness Heuristic: Average R^2 across Experts and Over Time

We examine the comovement of the representativeness heuristic on stock recommendations. Table 6 reports the mean, median, and standard deviation of each representativeness group's EW and VW R^2 , the skewness and kurtosis of the residual return, the recommendation times, the number of stocks included, the Sharpe ratio of recommending experts, and the portfolio's volatility. We observe that REP1 has the smallest R^2 , strongest right skew (indicating good firm-level news) and most recommendation by experts. Table 7 presents the results regarding the relationship between stock return synchronicity and its determinants. The various specifications distinguish the behavioral and fundamental views of comovement, and we run regressions with both EW and VW R^2 as dependent variables for each specification.

The results in the first four columns of Table 7 are consistent with our hypotheses H3a, H3b, and H3c. The former two columns demonstrate the comovement caused by representativeness, and the latter two columns reveal the comovement of the herding recommendation, controlling for kurtosis and the size variables. Stocks with high representativeness that gain nothing about firm-level news have high R^2 s. Stocks with more expert recommendations appear in more market-level news and thus have higher R^2 s. The herding recommendation emphasizes public

information, whereas representativeness privileges recent information. The comovement by the herding recommendation that catches more market-level news has a more marginal effect than the comovement by high representativeness. We use the Sharpe ratio to proxy experts' performance; as predicted, the coefficients of the Sharpe ratio are negative and significant. The experts with lower Sharpe ratios fail to capture the firm-specific variances and have high R^2 s. Skewness measures extreme firm-level news likelihood. The coefficient is negative and significant in the EW regressions but nonsignificant with VW regressions. A higher skewness indicates relatively more positive outliers in the distribution of residual returns. Positive skew is associated with lower R^2 s. The coefficients of kurtosis are negative which are significant in the regressions without the variable of representativeness. The stocks with high kurtosis (long tails in residual return distributions) have low R^2 s. Our findings demonstrate that the fundamental factor (the number of recommendations) has a more substantial impact than the behavior factor (representativeness) on the impact of stock synchronicity, according to both the t statistics of its coefficients and R^2 . Moreover, these specifications of the EW regressions have more explanatory power than the VW regressions do.

Columns 5 through 8 of Table 7 present the results after the addition as an additional independent variable of portfolio return volatility, which is a measurement of the variance of the five groups' returns in each period. Portfolio volatility is positively related to R^2 . Stocks within a high portfolio's return variability have high R^2 s, which is in accordance with our predictions. A higher portfolio's return variability means those stocks in the portfolio are more opaque, hard-to-value and difficult-to-arbitrage. The addition of portfolio volatility increases the t statistics for skewness, but reduces the t statistics for the Sharpe ratio. Kurtosis and the number of stocks play the same role as before. The final two columns of Table 7 report both the behavioral and fundamental views of comovement. All of these factors explain 52.3%–52.8% of stocks return synchronicity.

Table 6. Summary statistics for *representativeness heuristic* portfolios

Group/Quarters in sample		Equal- weighted R^2	Variance- weighted R^2	Skewness	Kurtosis	# of recommended	Log(# of stock)	Sharp ratio	Portfolio's variability
REP1 $Q = 19$	Mean	-0.934	-0.921	0.544	6.347	1.641	4.975	0.197	1.424
	Median	-0.878	-0.964	0.523	5.571	1.593	4.804	0.342	1.424
	Std. Dev.	0.284	0.288	0.458	2.161	0.306	0.398	0.021	0.131
REP2 $Q = 19$	Mean	-0.883	-0.861	0.412	5.053	1.429	4.772	0.690	1.389
	Median	-0.917	-0.929	0.385	4.794	1.362	4.571	0.245	1.396
	Std. Dev.	0.262	0.278	0.436	1.142	0.207	0.494	0.033	0.105
REP3 $Q = 19$	Mean	-0.753	-0.730	0.412	4.726	1.337	4.261	0.460	1.451
	Median	-0.743	-0.761	0.478	4.461	1.278	4.043	0.001	1.489
	Std. Dev.	0.198	0.203	0.384	1.307	0.197	0.670	0.029	0.136
REP4 $Q = 19$	Mean	-0.677	-0.662	0.562	3.970	1.302	3.389	0.235	1.450
	Median	-0.528	-0.586	0.583	3.694	1.287	3.296	0.100	1.509
	Std. Dev.	0.311	0.327	0.381	1.303	0.177	0.758	0.069	0.194
REP5 $Q = 19$	Mean	-0.556	-0.545	0.318	3.191	1.188	2.522	-0.503	1.473
	Median	-0.362	-0.312	0.362	3.064	1.190	2.586	-0.692	1.502
	Std. Dev.	0.519	0.532	0.443	1.076	0.121	0.453	0.020	0.295

This table summarizes statistics for five *representativeness heuristic* portfolios, including equal-weighted and variance-weighted R^2 , the mean of the skewness and kurtosis of the residual return, the average of the recommendation times, the number of stocks including, the sharp ratio of recommending experts, and portfolio's return variability.

Table 7. Explaining differences in *representativeness* heuristic groups-average R^2 s across experts and over time

Logistic(R^2) Variable	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
RepreID	0.154*** (3.295)	0.171*** (3.591)			0.152*** (3.237)	0.168*** (3.532)			0.119** (2.564)	0.136*** (2.938)
# of recommended			0.908*** (5.271)	0.924*** (4.855)			0.874*** (4.750)	0.881*** (4.382)	0.746*** (4.405)	0.736*** (4.182)
Sharp ratio	-0.015*** (-3.723)	-0.013*** (-3.106)	-0.016*** (-3.488)	-0.014*** (-2.917)	-0.009** (-2.164)	-0.005 (-1.265)	-0.010** (-2.529)	-0.007 (-1.526)	-0.008* (-1.752)	-0.004 (-0.912)
Skewness	-0.158** (-2.019)	-0.131 (-1.647)	-0.118* (-1.755)	-0.094 (-1.330)	-0.223*** (-2.804)	-0.211** (-2.492)	-0.179** (-2.607)	-0.171* (-2.216)	-0.162** (-2.584)	-0.151** (-2.207)
Kurtosis	-0.011 (-0.604)	-0.017 (-0.941)	-0.038* (-1.925)	-0.047** (-2.366)	-0.006 (-0.298)	-0.011 (-0.569)	-0.033* (-1.674)	-0.040** (-2.070)	-0.021 (-1.060)	-0.026 (-1.320)
Portfolio volatility					0.470*** (3.372)	0.576*** (4.050)	0.425*** (3.291)	0.532*** (3.909)	0.419*** (3.517)	0.526*** (4.167)
Log(# of stock)	0.083 (1.496)	0.119** (2.113)	-0.231*** (-4.889)	-0.214*** (-4.047)	0.089 (1.623)	0.127** (2.247)	-0.217*** (-4.768)	-0.197*** (-3.975)	-0.073 (-0.954)	-0.033 (-0.418)
Average Adj. R^2	0.349	0.329	0.412	0.363	0.412	0.407	0.454	0.429	0.528	0.523
Sample size	94	94	94	94	94	94	94	94	94	94

The dependent variables are logistic transformations of equal-weighted (EW) or variance-weighted (VW) R^2 s. The explanatory variables are the expert's sharp ratio, the log of the mean of stocks size, the log of the number of stocks covered in each expert monthly, the monthly value of skewness and kurtosis from residual returns, and portfolio volatility. Coefficients are estimated by Fama-MacBeth (1973) method and further adjusted for serial correlation of coefficient estimates following Pontiff (1996). The t -statistics are reported in parentheses and based on Newey and West (1994) method for heteroskedasticity-consistent standard errors. Three, two and one asterisks (*) denote the significance of the correlation coefficient at the 0.01, 0.05, and 0.10 levels, respectively.

5. Conclusion

In this paper, we examine whether experts in investment magazines exhibit cognitive bias in stock recommendations and how their recommended stocks performed in the Taiwanese stock market. Our paper has implications for academics and investors. We add to the academic literature on the behavior of the best performance financial experts. Thus, investors can refer the way of stocks selection by the superior experts. The empirical results show that high-performing experts demonstrate less representativeness than low-performing experts do. Because of limited attention and processing power, stocks recommended by high media exposure and high win probability experts are viewed as new useful information by other experts when they make recommendations the following week.

We next analyze experts' behavior and stock recommendations under various sentiments and market statuses. Experts exhibit more herding recommendations and representativeness under pessimistic sentiment and during bull market periods. According to abnormal return analysis, more representative stocks have lower abnormal returns. However, for high-performing experts, including a small amount of representativeness bias in recommendations yields a greater abnormal return than completely avoiding representativeness does. Therefore, high-performing experts should strategically make a few representativeness recommendations.

Regarding the contribution of market-level news, consistent with our hypotheses, both the representativeness and herding recommendations lead to higher stock price comovement. Representativeness comovement is due to increased noise and decreased firm-level news, whereas herding recommendations is caused by more market-level information. The situation is consistent with Keynes' beauty contest, in which recommenders incorporate the expected recommendations of others into their own recommendations. This is because the common recommendation across experts is a key determinant of asset price. When the common recommendation determines asset prices, individual experts rely on the expected consensus recommendation when making their own recommendations; individual experts will overweight public signals and underweight private signals (Allen et al., 2006). Because the herding recommendation is the summary of individual recommendations and individual recommendations are biased because of public information overweighting, the consensus will be a biased predictor as well. Hence, investors should not expect higher-herding recommendation to contain useful information regarding firm-level news. Overall, our study suggests that investors should refer more on stock recommendations by high-performing experts and buy the stocks recommended by more experts. Furthermore, both experts and investors should not be involved into representativeness when making investment decisions.

References

- Allen, F., Morris, S., & Shin, H.S. (2006). Beauty contests and iterated expectations in asset markets. *Review of Financial Studies*, 19, 719-752. <http://dx.doi.org/10.1093/rfs/hhj036>
- Akhtar, S., Faff, R., Oliver, B., & Subrahmanyam, A. (2012). Stock salience and the asymmetric market effect of consumer sentiment news. *Journal of Banking & Finance*, 36, 3289-3301. <http://dx.doi.org/10.1016/j.jbankfin.2013.07.032>
- Baker, H. K., & Ricciardi, V. (2014). *Investor behavior -the psychology of financial planning and investing*. Hoboken, NJ: John Wiley & Sons. <http://dx.doi.org/10.1002/9781118813454.ch25>
- Baker, M., Wurgler, J., & Yu, Y., (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, 104, 272-287. <http://dx.doi.org/10.1016/j.jfineco.2011.11.002>
- Barberis, N. (2013). Psychology and the financial crisis of 2007-2008. In: Haliassos, M. (Ed.), *Financial Innovation: Too Much or Too Little?* MIT Press, Cambridge. <http://dx.doi.org/10.7551/mitpress/9780262018296.003.0002>
- Barberis, N. & Shleifer, A. (2003). Style investing. *Journal of Financial Economics*, 68, 161-199. [http://dx.doi.org/10.1016/S0304-405X\(03\)00064-3](http://dx.doi.org/10.1016/S0304-405X(03)00064-3)
- Bonner, S. E., Hugon, A., & Walther, B. R. (2007). Investor reaction to celebrity analysts: the case of earnings forecast revisions. *Journal of Accounting Research*, 45, 481-513. <http://dx.doi.org/10.1111/j.1475-679X.2007.00245.x>
- Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52, 57-82. <http://dx.doi.org/10.2307/2329556>
- Chen, C. C., Kuo, Y. C., Huang, C. H., & Chen, A. P. (2014). Applying market profile theory to forecast Taiwan Index Futures market. *Expert Systems with Applications*, 41, 4617-4624. <http://dx.doi.org/10.1016/j.eswa.2013.08.093>
- Corredor, P., Ferrer, E., & Santamaria, R. (2014). Is cognitive bias really present in analyst forecasts? The role of investor sentiment. *International Business Review*, 23, 824-837. <http://dx.doi.org/10.1016/j.ibusrev.2014.01.001>
- Ertimur, Y., Muslu, V., & Zhang, F. (2011). Why are recommendations optimistic? Evidence from analyst coverage initiations. *Review of Accounting Studies*, 16, 679-718. <http://dx.doi.org/10.1007/s11142-011-9163-6>
- Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81, 607-636. <http://dx.doi.org/10.1086/260061>
- Fang, L.H., & Yasuda, A. (2014). Are stars' opinions worth more? the relation between analyst reputation and recommendation values. *Journal of Financial Services Research*, 46, 235-269. <http://dx.doi.org/10.1007/s10693-013-0178-y>
- Gleason, K.C., Mathur, I., & Peterson, M.A. (2004). Analysis of intraday herd behavior among the sector ETFs. *Journal of Empirical Finance*, 11, 681-694. <http://dx.doi.org/10.1016/j.jempfin.2003.06.003>
- Hillert, A., Jacobs, H., & Müller, S. (2014). Media Makes Momentum, *Review of Financial Studies*, 27, 3467-3501. <http://dx.doi.org/10.1093/rfs/hhu061>
- Hoffmann, A.O.I., Post, T., & Pennings, J.M.E. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, 37, 60-74. <http://dx.doi.org/10.1016/j.jbankfin.2012.08.007>
- Hribar, P., & McNinnis, J. (2012). Investor sentiment and analysts' earnings forecast errors. *Management Science*, 58, 293-307. <http://dx.doi.org/10.1287/mnsc.1110.1356>
- Jegadeesh, N., & Kim, W. (2010). Do analysts herd? An analysis of recommendations and market reactions. *Review of Financial Studies*, 23, 901-937. <http://dx.doi.org/10.1093/rfs/hhp093>
- Jin, Li, & Myers, S. 2006, R² around the world: New theory and new tests, *Journal of Financial Economics*, 79, 257-292. <http://dx.doi.org/10.1016/j.jfineco.2004.11.003>
- Loh, R. K., & Stulz, R. M. (2011). When are analyst recommendation changes influential? *Review of Financial Studies*, 24, 593-627. <http://dx.doi.org/10.1093/rfs/hhq094>
- Luo G. Y. (2013). Can representativeness heuristic traders survive in a competitive securities market? *Journal of Financial Markets*, 16, 152-164 <http://dx.doi.org/10.1016/j.finmar.2012.05.001>
- Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: why do emerging markets have

- synchronous stock price movements? *Journal of Financial Economics*, 58, 215-260. [http://dx.doi.org/10.1016/S0304-405X\(00\)00071-4](http://dx.doi.org/10.1016/S0304-405X(00)00071-4)
- Pontiff, J., 1996. Costly arbitrage: evidence from closed-end funds. *Quarterly Journal of Economics*, 111, 1135-1151. <http://dx.doi.org/10.2307/2946710>
- Rangvid, J., Schmeling, M., & Schrimpf, A. (2013). What do professional forecasters' stock market expectations tell us about herding, information extraction and beauty contests? *Journal of Empirical Finance*, 20, 109-129. <http://dx.doi.org/10.1016/j.jempfin.2012.11.004>
- Riasi, A. (2015). Competitive Advantages of Shadow Banking Industry: An Analysis Using Porter Diamond Model. *Business Management and Strategy*, 6(2), 15-27. <http://dx.doi.org/10.5296/bms.v6i2.8334>
- Shiller, R.J. (2005). *Irrational Exuberance*. 2nd edition, Princeton University Press. <http://dx.doi.org/10.1515/9781400865536-003>
- Xu, N., Chan, K.C., Jiang, X., & Yi, Z. (2013). Do star analysts know more firm-specific information? Evidence from China. *Journal of Banking & Finance*, 37, 89-102. <http://dx.doi.org/10.1016/j.jbankfin.2012.08.014>

Notes

Note 1. Unlike the sell-side analyst or buy-side analyst, magazine expert is the independent analyst.

Note 2. Salient firms are firms whose securities are prominent or even “iconic” in the market. Market prominence can be linked to firms with a greater presence in the minds of investors because they have, for example, high analyst coverage or high media exposure.

Note 3. According to the ranking of financial and business magazines provided by Kingstone bookstore, *Marbo* and *Wealth Invest Weekly* are within the top two positions.

Note 4. Bonner, Hugon, and Walther (2007) use the quantity of media coverage analysts receive as our empirical proxy for celebrity.

Note 5. These foreign firms are affected by their home country, and the IPO's stocks have abnormal returns.

Note 6. Because the log of the number of stocks recommended and the size of the stocks have a high correlation (0.66), and the former variable has more explanatory power for stock synchronicity. We leave the log of the number of stocks recommended to the latter analysis.

Note 7. The result is unchanged if a nonparametric test is used. We present the results of parametric approaches latter.