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Self-attribution bias in consumer financial decision-making: How investment returns affect individuals' belief in skill☆

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ABSTRACT

Self-attribution bias is a long-standing concept in psychology research and refers to individuals' tendency to attribute successes to personal skills and failures to factors beyond their control. Recently, this bias is also being studied in household finance research and is considered to underlie and reinforce investor overconfidence. To date, however, the existence of self-attribution bias amongst individual investors is not directly empirically tested. That is, it remains unclear whether good (vs. bad) returns indeed make investors believe more (vs. less) strongly that skills drive their performance. Using a unique combination of survey data and matching trading records of a sample of clients from a large discount brokerage firm, we find that (1) the higher the returns in a previous period are, the more investors agree with a statement claiming that their recent performance accurately reflects their investment skills (and vice versa); and (2) while individual returns relate to more agreement, market returns have no such effect.

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1. Introduction

Self-attribution bias is a long-standing concept in psychology research and refers to individuals' general tendency to attribute successes to personal skills and failures to factors beyond their control (see e.g., Feather and Simon, 1971; Miller and Ross, 1975). Recently, self-attribution bias is also gaining research attention in the field of household finance. In this regard, this bias is thought to underlie and reinforce individual investor overconfidence (Barber and Odean, 2002; Dorn and Huberman, 2005). The household finance literature demonstrates that investor overconfidence is associated with such behaviors as overtrading (Barber and Odean, 2002) and underdiversification (Goetzmann and Kumar, 2008), which are detrimental to consumer financial well-being because they lead to underperformance and portfolios with high idiosyncratic risk.

For the above-mentioned reasons, it is important to increase the understanding of self-attribution bias in the context of consumer financial decision-making. To date, however, the existence of self-attribution bias amongst individual investors is only assumed and not directly empirically tested. For example, it is presumed that self-attribution bias causes successful investors to grow increasingly overconfident about their investment skills and therefore increase their trading volume over time (Daniel et al., 1998; Gervais and Odeam, 2001; Statman et al., 2006). Whether individual investors actually have a self-attribution bias, however, is not measured in such studies. As a notable exception, (Dorn and Huberman, 2005) survey a sample of individual investors about whether they judge their past investment successes to be mainly due to their personal skills. However, they do not test whether these investors indeed attribute good returns to their skills and bad returns to other factors. As such return attribution forms an essential component of self-attribution bias (Miller and Ross, 1975), the absence of a direct test in this regard is an important limitation of previous literature.

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The present research establishes direct empirical evidence for self-attribution bias in consumer financial decision-making using a unique combination of survey data and matched trading records of a sample of Dutch discount brokerage clients. In so doing, the current research contributes to the emerging literature that examines how consumers make financial decisions and manage their personal wealth (Zhou and Pham, 2004; Johnson et al., 2005; He et al., 2008; Lee et al., 2008; Hoffmann and Broekhuizen, 2010; Strahilevitz et al., 2011; Aspara and Hoffmann, 2013). Considering the population's aging demographics and individuals' increasing self-responsibility for accumulating retirement wealth (van Rooij, Lusardi, and Alessie, 2011), household finance is of growing importance (Campbell, 2006; Lynch, 2011). Indeed, according to Zhou and Pham (2004), no theory of consumption is complete without a fundamental psychological understanding of why individuals manage their wealth in the ways they do. The present research aims to contribute to this understanding.

To establish the presence of self-attribution bias, the extant literature argues that it must be shown that individuals indulge in both self-protective attributions under conditions of failure and self-enhancing attributions under conditions of success (see Miller and Ross, 1975: 214). In the context of the present research (i.e., individual investor decision-making), this means that individuals would have to attribute their recent investment performance more (vs. less) to their personal skills when the outcome is good (vs. bad). Testing this notion requires data on both a (survey) measure of investor performance self-attribution and matched (brokerage) data on actual individual investment performance. The current research is fortunate to have access to both types of data, in the form of investors' self-reported performance attributions gauged by an online survey combined with individual-level returns of the same individuals obtained through their brokerage records. Using these data, this research tests two related hypotheses.

First, we expect a positive relationship between investment returns in a given period and investors' agreement at the end of the period with a statement claiming that their recent performance reflects their personal investment skills (H1a). Second, considering that self-attribution bias relates to taking (vs. not taking) responsibility for personal successes or failures (see Glaser and Weber, 2009) for a discussion on the potential differential impact of individual vs. market returns), we expect that only individual-level investment returns affect investors' agreement with the above-mentioned statement, while market returns have no such effect (H1b).

The remainder of this paper is organized as follows. Section 2 describes the data that we use to test the above-mentioned hypotheses. Section 3 presents empirical results. Section 4 concludes the paper, discusses implications for practitioners, and provides avenues for future research.

2. Data

We test the hypotheses using a unique panel dataset combining survey data with matching brokerage records of clients of a large Dutch discount broker. Hoffmann, Post, and Pennings, (2013) also use this dataset. Variables used in the analyses are defined in the notes of Table 1.

2.1. Survey data

In April 2008, we invited per email 20,000 randomly selected brokerage clients to participate in an investor panel. About 4% of the invited clients agreed to become part of the panel and to receive an email at the end of each month between April 2008 and March 2009 in which they were requested to follow a link to complete an online survey. The initial response rate of 4% for April 2008 is comparable to that of similar investor surveys (cf. Dorn and Sengmueller, 2009). Nevertheless, Hoffmann et al. (2013) compare the investors in the sample who complete the survey to the broker's overall client base to check for a potential response bias. This comparison indicates that the sample is not subject to any non-random response problems (see also the results of an additional robustness check as reported in Table 2 in Section 3).[1] Another possible concern is response timing potentially affecting the results. That is, the self-attribution bias of early versus late respondents to the monthly investor survey might differ, because of changes in individual portfolio returns between their response times. As we receive most responses within the first few days after sending out each survey email, however, it is unlikely that there is a response-time pattern that could introduce a possible bias. A check that excludes late respondents by Hoffmann et al. (2013) confirms that response timing is of no concern.

In April–June 2008, the monthly investor survey included a question measuring individuals' self-attribution regarding their last month's investment performance. In particular, we asked brokerage clients to indicate the extent of their agreement with the following statement: "The recent performance of my investment portfolio accurately reflects my investment skills." Clients were asked to provide their response to this statement by selecting an integer value from a seven-point Likert scale, which was labeled as follows: 1 = "completely disagree"; 4 = "neutral"; 7 = "completely agree." The remaining points on the scale (i.e., 2, 3, 5, and 6) were labeled exclusively with their respective number. Low scores on this henceforth called Self-Attribution Scale (SAS) indicate that individuals take no personal responsibility for their recent investment performance, while high scores indicate that individuals attribute their recent investment performance to their own investment skills. The mean of the responses for SAS over the 3 months of April–June 2008 is 3.72 (SD = 1.43). Our measurement of self-attribution regarding investment performance is consistent with that of Dorn and Huberman (Dorn and Huberman, 2005), who asked survey participants about their agreement with the following statement: "My past investment successes were, above all, due to my specific skills." Note, however, that these authors did not test whether investors indeed attribute good returns to their skills and bad returns to other factors, which is an essential component of self-attribution bias (Miller and Ross, 1975).

2.2. Brokerage records

We have access to the brokerage records of clients who completed at least one survey during the sample period. In particular, we have survey data and matched brokerage records available for 787 clients in April, 701 clients in May, and 605 clients in June (total number of client-month observations = 2093; number of distinct investors in the sample = 866). As of April 2008, the mean age of these clients is 50.55 years (SD = 13.51 years), 93% (7%) of them is male (female), and their average portfolio value is €54,446

[1] In particular, we apply an inverse-probability-weighted estimator as a robustness check (Robins and Rotnitzky, 1995; Wooldridge, 2002). For each of the three months, a logit model is estimated where the dependent variable indicates either response (1) or non-response (0) to the survey. As explanatory variables, we include Gender, Age, and Account Tenure. Next, the predicted probabilities of survey response are calculated. Finally, the regression models of Section 3 are estimated again using the inverse of the predicted probabilities as sample weights. The results of the regressions that include this estimator are similar to those obtained from the original specifications in terms of coefficient magnitudes, significance, and signs (detailed results available from the authors upon request).

Table 1
Regression results explaining investors' SAS scores by portfolio and market returns.

Dependent variable	Self-attribution (SAS) (1)			Self-attribution (SAS) (2)			Self-attribution (SAS) (3)			Self-attribution (SAS) (4)			Self-attribution (SAS) (5)		
	Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.	
Portfolio return	0.505	0.109	***	0.389	0.124	***	0.412	0.230	*	0.597	0.087	***	0.423	0.145	***
Self-attribution (SAS) t^{-1}										0.200	0.042	***	0.201	0.042	***
AEX index return													0.764	0.501	
Gender				0.052	0.146		0.107	0.184		0.020	0.187		0.026	0.185	
Age				−0.009	0.003	***	−0.009	0.004	**	−0.010	0.003	***	−0.010	0.003	***
Account tenure				0.051	0.012	***	0.062	0.017	***	0.039	0.017	**	0.040	0.017	**
ln(Income)				−0.119	0.374		−0.244	0.401		−0.687	0.150	***	−0.687	0.159	***
ln(Avg. portfolio value)				0.072	0.021	***	0.090	0.032	***	0.040	0.024		0.042	0.025	*
ln(House value)				0.081	0.091		0.145	0.179		0.201	0.049	***	0.195	0.055	***
Constant	3.611	0.183	***	3.386	3.010					7.419	0.995	***	7.471	0.949	***
$\kappa 1$							−2.415								
$\kappa 2$							−1.263								
$\kappa 3$							−0.242								
$\kappa 4$							1.323								
$\kappa 5$							2.167								
$\kappa 6$							3.296								
N observations	2093			2093			2093			1167			1167		
N investors	866			866			866			678			678		
Log-likelihood							−3565								
R^2	0.007			0.028						0.084			0.085		

This table presents the results from regressions of investors' Self-Attribution Scale (SAS) scores on: past investor returns (Model 1); past investor returns and a set of control variables (Models 2 and 3); past investor returns, lagged SAS, and a set of control variables (Model 4); and past investor returns, past market index (AEX) returns, lagged SAS, and a set of control variables (Model 5). That is, we regress an investor's monthly (=end-of-the-month) SAS score on the respective returns achieved in each month. Columns 1, 2, 4, and 5 show results of linear panel models ($y_{it} = \alpha + x'_{it}\beta + e_{it}$). Column 3 shows results from an ordered logit model ($\ln(\theta_j) = \kappa_j - x'\beta$, with $\theta_j = \Pr(y \leq j)/\Pr(y > j)$). The number of individual investors included in Models (4) and (5) (678) is smaller than that in Models (1)–(3) (866), because not all investors responded to the survey for two consecutive months. Self-Attribution (SAS) indicates investors' response to the statement: "The recent performance of my investment portfolio accurately reflects my investment skills." Clients were asked to provide their response to this statement by selecting an integer value from a seven-point Likert scale, which was labeled as follows: 1 = "completely disagree"; 4 = "neutral"; 7 = "completely agree." The remaining points on the scale (i.e., 2, 3, 5, and 6) were labeled exclusively with their respective number. Portfolio return is the monthly investor return given by the product of the daily relative changes in the value of an individual's portfolio, after transaction costs, and adjusting for portfolio in- and outflows. AEX Index Return is the monthly return on the Dutch stock market index AEX. Gender is an indicator variable taking the value 0 for male investors and 1 for female investors. Age is the age of the investor in years as of April 2008. Account tenure is the investor's account tenure in years as of April 2008. Ln(Income) is the natural log of an investor's annual disposable income in 2007 (equals gross income minus taxes, social security contributions, and health-insurance premiums paid) that is assigned to each investor based on his or her 6-digit postal code. Data source is the average net income per 6-digit postal code from Statistics Netherlands (Central Bureau of Statistics). Ln(Avg. Portfolio Value) is the average value of the investment assets in an investor's account. Ln(House Value) is the natural log of the value of an investor's house in 2008, which is assigned to each investor based on his or her 6-digit postal code. Data source is the average residential house value per 6-digit postal code from Statistics Netherlands. Standard errors are clustered by investor and month.

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Table 2
Regression results explaining investors' SAS scores–controlling for selection effects.

Self-Attribution Score						
Dependent variable	Self-attribution (SAS) (1)			Self-attribution (SAS) (2)		
	Coef.	Std. err.		Coef.	Std. err.	
Portfolio return	0.301	0.137	**	0.213	0.108	**
Gender	0.035	0.110		0.037	0.072	
Account tenure	0.034	0.010	***	0.032	0.007	***
ln(Income)	−0.173	0.225		−0.115	0.163	
ln(Avg. portfolio value)	0.041	0.018	**	0.043	0.011	***
ln(House value)	0.085	0.104		0.060	0.084	
Constant						
$\kappa1$	−1.532			−0.278		
$\kappa2$	−0.912			0.208		
$\kappa3$	−0.297			0.698		
$\kappa4$	0.658			1.479		
$\kappa5$	1.124			1.871		
$\kappa6$	1.669			2.341		

Survey participation				
Dependent variable		Survey participation		
		Coef.	Std. err.	
Gender		0.007	0.036	
Age		0.007	0.001	***
Account tenure		0.006	0.004	*
Constant		−0.809	0.039	***
rho			0.687	
N observations (SAS)	2093		2093	
N investors (SAS)	866		866	
Log-likelihood	−3569		−14,713	

This table presents the results from regressions of investors' Self-Attribution Scale (SAS) scores on past investor returns and a set of control variables. That is, we regress an investor's monthly (=end-of-the-month) SAS score on the respective returns achieved in each month. Column 1 shows results from an ordered probit model ($\Phi^{-1}(\theta_j) = \kappa_j - x'\beta$, with $\theta_j = \Pr(y \le j)$), and column 2 shows results from an ordered probit model with sample selection (full information maximum likelihood estimation). Self-Attribution (SAS) indicates investors' response to the statement: "The recent performance of my investment portfolio accurately reflects my investment skills." Clients were asked to provide their response to this statement by selecting an integer value from a seven-point Likert scale, which was labeled as follows: 1 = "completely disagree"; 4 = "neutral"; 7 = "completely agree." The remaining points on the scale (i.e., 2, 3, 5, and 6) were labeled exclusively with their respective number. Portfolio return is the monthly investor return given by the product of the daily relative changes in the value of an individual's portfolio, after transaction costs, and adjusting for portfolio in- and outflows. Gender is an indicator variable taking the value 0 for male investors and 1 for female investors. Age is the age of the investor in years as of April 2008. Account tenure is the investor's account tenure in years as of April 2008. Ln(Income) is the natural log of an investor's annual disposable income in 2007 (equals gross income minus taxes, social security contributions, and health-insurance premiums paid) that is assigned to each investor based on his or her 6-digit postal code. Data source is the average net income per 6-digit postal code from Statistics Netherlands (Central Bureau of Statistics). Ln(Avg. Portfolio Value) is the average value of the investment assets in an investor's account. Ln(House Value) is the natural log of the value of an investor's house in 2008, which is assigned to each investor based on his or her 6-digit postal code. Data source is the average residential house value per 6-digit postal code from Statistics Netherlands. Survey Participation is an indicator variable taking the value 1 if an investor participated in the survey in a particular month and 0 otherwise.

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

(SD = €143,872). As to the representativeness of our sample, the age, gender, and portfolio values are similar to those of the samples used in related household finance studies in the United States (Barber and Odean, 2000) and the Netherlands (Bauer, Cosemans, and Eichholtz, 2009). Moreover, comparing the average portfolio value of the clients in our sample to the average portfolio value of Dutch individual investors in general (which is about €50,000–60,000 according to a report of the market research agency Millward-Brown (2006)) suggests that the average client in

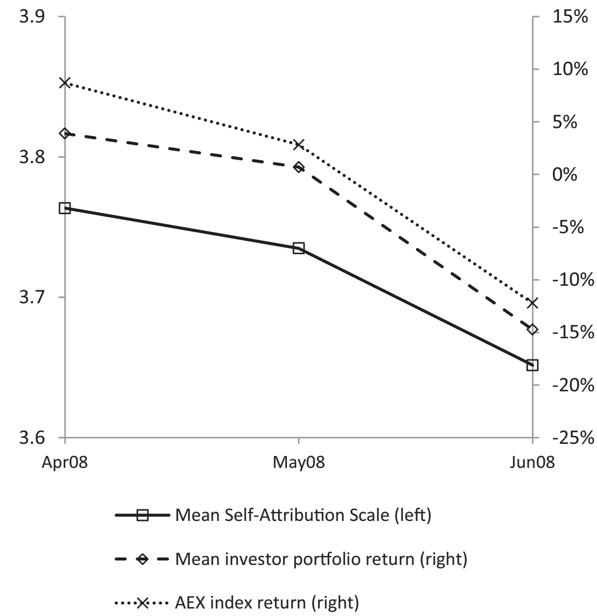

Fig. 1. Mean Self-Attribution Scale (SAS) score, portfolio returns, and market returns.

our sample invests more than three-fourths of his or her total self-managed investment portfolio with this particular Dutch discount broker.

3. Results

Hypothesis H1a predicts a positive relationship between an individual's investment returns in a given period and that investor's SAS score, which measures the extent to which individuals judge their recent investment performance as reflecting their personal investment skills. Investment returns are calculated as the product of the daily relative changes in the value of an investor's portfolio, after transaction costs, and adjusting for any portfolio in- and outflows. Since we measure the SAS at the end of each month, we relate an investor's SAS score to the particular returns that this investor experienced within this month. Fig. 1 plots the mean SAS score of the sample of investors at the end of each of the 3 months (i.e., April–June 2008), as well as the mean of investors' portfolio returns and those of the Dutch market index (AEX) realized within each respective month. Fig. 1 shows that, on average, the SAS score moves in tandem with both the individual portfolio returns of investors in the sample as well as with market returns. That is, with decreasing return performance over the three months, the mean SAS score also decreased. It thus seems that with decreasing returns, individuals take less personal responsibility (in terms of skills) for their investment performance.

To obtain statistical evidence on whether realized individual portfolio returns are indeed positively related to investors' SAS scores, thus indicating that their performance attribution would be biased in a way that is consistent with our hypotheses, we examine the cross-sectional and time-series variation in SAS scores and returns. In particular, we first estimate a linear panel regression (Model 1) with investors' SAS scores (measured at the end of a month) as the dependent variable and investors' portfolio returns as the independent variable (that is, the returns achieved during the respective month). We cluster standard errors by investor and month. Following the extant literature in household finance (see e.g., Dorn and Huberman, 2005), we next include a set of investor characteristics (gender, age, account tenure, income, house value, portfolio value) as control variables (Model 2). Models (1) and (2) in Table 1 contain the respective linear panel regression results and demonstrate that the portfolio returns that an investor achieved in a particular month are indeed positively and significantly related to his or her SAS score at the end of that month, thus providing support for hypothesis H1a.[2] As an alternative, Model (3) uses an ordered logit model and confirms the effects we found previously.

Note that although we control for various investor characteristics in Model (2), it is not yet clear whether portfolio returns indeed drive investors' SAS scores, or that for various other reasons (e.g., differences in investment strategy related to differences in SAS scores) investors that score high (vs. low) on the SAS have higher (vs. lower) returns. The within-investor time-series correlation of SAS, that is, the correlation of an investor's SAS score at time t with the SAS score at time $t^{-1} = 0.24$ ($p = 0.00$). Accordingly, it might be that SAS is rather stable within investors and is related to portfolio returns for reasons other than self-attribution bias. To account for this possibility, we include the one-period lagged value of SAS in Model (4) (Table 1). Thus, we now separate out the impact of portfolio returns on the update in an investor's SAS score, that is, the part of the SAS score that is driven by the recent returns that an investor has achieved. The results of Model (4) confirm the previous evidence. That is, although SAS scores are to some extent stable within investors (the regression coefficient for past SAS score = 0.20, $p = 0.04$), SAS scores are significantly and positively driven by an investor's achieved portfolio returns. Moreover, high past values for SAS do not predict high returns. Regressing returns in a given month on the lagged value of SAS yields an insignificant coefficient of −0.002 ($p = 0.65$) for past levels of SAS (detailed results available from the authors upon request). That is, the positive relation between returns and SAS is driven by returns, that is, self-attribution bias, but not by a potential alternative explanation according to which investors with higher scores of SAS would have superior investment skills and thus obtain higher returns.

Hypothesis H1b predicts that there is only a positive relationship between individual-level investment returns in a given period and an investor's SAS score, while aggregate market returns in a given period have no relationship with an investor's SAS score. To test H1b, we include the monthly returns of the Dutch market index (AEX) as an additional independent variable in Model (5) (Table 1). In support of hypothesis H1b, the regression results indicate that market returns in a particular month indeed have no significant impact on an investor's SAS score at the end of that month, while the effect of individual returns in a particular month on an investor's SAS score remains significant and positive, as shown previously for the Models (1), (2), and (4).

To control for sample selection effects, we additionally estimate an ordered probit model with endogenous sample selection (Model (2) in Table 2). Following Hoffmann et al. (2013), the variables gender, age, and account tenure are used to predict survey participation. As the results of Model (2) in Table 2 cannot be directly compared to those of the ordered logit model in Table 1 (Model 3), we also provide the results from a standard ordered probit model in Table 2 (Model 1). Comparing the results from both ordered probit models in Table 2 indicates that our results are robust to sample selection effects. That is, although the coefficient size for investors returns is smaller in Model (2) than Model (1), it is still positive and significant at the 5% level.

[2] Alternative model specifications that regress SAS on a discrete dummy variable indicating whether investors had a positive return (=1 and 0 otherwise), yield supporting evidence. The coefficient for this dummy is +0.13 ($p = 0.03$).

4. Conclusion

By presenting direct empirical evidence for the presence of self-attribution bias in an individual investor context, the current research contributes to the emerging literature on household finance. In particular, while previous work in this field assumes the existence of self-attribution bias and how an individual's investment performance relates to it, the current research uses a unique combination of survey data and matching trading records of a large Dutch discount broker to demonstrate how individual portfolio returns actually affect investors' scores on a survey measure of self-attribution bias. In this regard, the results show that the higher previous period's returns are, the more investors agree with a statement claiming that their recent performance accurately reflects their investment skills. Moreover, while individual returns relate to such agreement, market returns do not have an impact on investors' agreement with this statement.

In terms of practical implications, financial advisors and policy makers may encourage consumers to educate themselves about the impact of their trading behavior on their investment performance, to help them understand the detrimental effects of such investment behaviors as overtrading or underdiversification, and to reduce such tendencies as attributing only particular subsets of investment outcomes to factors within (vs. beyond) their control. Overcoming self-attribution bias is important, as this bias may prevent investors to learn from their mistakes, as they simply attribute bad returns to factors beyond their control. In this regard, online decision-support systems may prove to be helpful (see e.g., Goldstein, Johnson, and Sharpe, 2008; Looney and Hardin, 2009). Indeed, considering the recent shift away from the traditional commission-based remuneration model toward a fee-based model for financial advice (see e.g., Bhattacharya et al., 2012; Hackethal et al., 2012; Hoffmann, Franken, and Broekhuizen, 2012), successfully providing high-quality, independent financial advice through a user-friendly (online) interface may prove to generate a competitive advantage for financial services firms.

Related to the practical implications as discussed above, follow-up research could examine how different behavioral nudges can support consumers in overcoming behavioral biases in their financial decision-making and test how these nudges differ in the extent of their effectiveness (see Thaler and Sunstein, 2008). Moreover, it might be interesting to examine the cross-cultural generalizability of our findings. In particular, while the current study involves investors from a Western industrialized nation (i.e., the Netherlands), the results may be different in an emerging market economy such as China (see Chen et al. (2007) for a comparison of behavioral biases between U.S. and Chinese investors). Indeed, prior research suggests that cultural differences in terms of individualism versus collectivism can affect individuals' outcome attributions (see e.g., Markus and Kitayama, 1991). Such differences could lead to cross-cultural differences regarding investors' tendency to engage in self-attribution bias. In this regard, research by Yan and Gaier (1994) as well as Heine and Hamaura (2007) suggest that people from Eastern cultures display a weaker self-serving bias than do people from Western cultures. Future research could examine whether these differences in self-attribution bias are also present in an investment context. Finally, the sample period of the present study (April–June 2008) corresponds to a time of considerable market volatility and uncertainty. The findings of Zhang (2006) suggest that high uncertainty can trigger individuals to be more prone to behavioral biases, such as overconfidence. Although our literature review indicates that self-attribution bias is a robust phenomenon that can be observed across different samples and time periods, future research is called for to establish the robustness of our findings across samples using different time periods.

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