Chapter 4

Factors that Affect Investment Decision-Making Behaviour: Findings from a Survey

4.1. Introduction

The previous chapter discussed the design and conduct of a mixed methods research approach; where the results from a survey questionnaire would be supplemented with actual observations from case studies on unauthorised trading activities in the examination of the research problem. The aim was to achieve a better understanding of the motivation and factors behind the irrational investment behaviour of investors, particularly investment professionals. This chapter covered the quantitative element of the mixed methods approach.

This chapter, which discussed the findings from the survey, consisted of three main sections. The first section outlined the statistical techniques used in the analysis of the survey data. The second section provided a description of the respondents in the survey. The third section addressed the questions:

i. Are the survey results consistent with the predictions of prospect theory?
ii. Are investment professionals more rational than retail investors?
iii. Does experience mitigate the influence of behavioural biases?
iv. Are there any demographic and socio-economic predictors of financial decision-making behaviour?

4.2. Statistical Analysis

The statistical analysis was carried out using the Statistical Package for the Social Sciences (SPSS) version 11. Descriptive statistics such as percentages, means, medians and standard deviations were used to provide a profile of the respondents in the survey. Tests of independence, correlation and regression analyses were conducted using the chi-square test and binomial logistic regression respectively. The conventional $p<0.05$ level was used to indicate statistical significance, and where appropriate $0.05<p<0.10$ was used to indicate weak statistical association or effects.

Binomial logistic regression analysis had been recommended in situations where the criterion variable was binomial and where the predictor variables were either continuous and/or categorical in nature. This regression technique also made no assumptions about the distribution of the data in the sample, i.e. the data need not be normally distributed. Given the characteristics of the data collected and non-random sampling approach used, this statistical technique would be appropriate for this study.

Some of the applications of logistic regression analysis were to (i) predict the likelihood of occurrence of a characteristic or outcome (criterion variable), (ii) determine the importance of predictor variables in the model, and (iii) examine interaction effects from the combination of two or more predictor variables (Garson, 2009; Wuensch, 2009; Jaccard, 2001; Pampel, 2000). In addition to *p*-values, the odds ratio, estimated from the regression coefficients in the model, would be used to assess the strength of

the effect of the predictor variables on the behavioural bias. Peng, Lee and Ingersoll (2002) recommended that reporting of the results of the logistic regression analysis should include information on:

- the overall evaluation of the logistic model;
- goodness-of-fit statistics; and
- tests of significance and assessment of the odds ratio for individual predictors and interaction effects (where applicable).

4.2.1. Model-building Approach

The approach to building the logistic regression model for each behavioural bias under study involved a three-step process.

1. Univariate logistic regression analysis was initially performed to identify predictor variables with statistical significance at $p<0.10$ level for inclusion into the model.
2. Multivariate logistic regression analysis was then performed with an initial model formed by the predictor variables that were found to be significant from the univariate logistic regression analysis.
3. Addition of the other predictor variables and interaction terms of two or more predictor variables to come up with the final model.

The logistic regression analysis was performed using the ‘enter’ method. Predictor variables and interaction terms were added to the model one at a time. With each addition, the log-likelihood test was performed to determine whether or not the added variable or interaction term was significant in improving the model.

In the SPSS output for the logistic regression function, the log-likelihood statistic for the larger model was compared with that for the smaller or restricted model. If the chi-square test of the difference was found to be even weakly significant ($p<0.10$), the new variable or interaction term was accepted into the final model.

4.2.2. Model-fitting Guidelines

Almost all literature on regression analysis highlighted the importance of evaluating how well the predicted data from the model would match the actual data. This was because failure to address model fit could lead to misleading or incorrect conclusions. The following statistical indicators or tests were used to assess the adequacy of the logistic regression models in Section 4.7.

- Overall model evaluation
    - Omnibus test of model coefficients
    - Log-likelihood statistic
- Goodness-of-fit statistics
    - Hosmer and Lemeshow test
    - Validation of predicted probabilities from the classification table
- Statistical tests of individual predictors
    - Wald chi-square statistic

<u>Omnibus test of model coefficients</u>

This was an absolute measure of the validity of the model. The null hypothesis that was being tested was that the predictor variables did not significantly improve the prediction of the outcome compared with a constant-only model. The null hypothesis was rejected

when the *p*-value of the chi-square test was less than 0.05. Rejecting the null hypothesis meant that there was adequate fit of the data to the model or that at least one of the predictors was significantly related to the criterion variable (Garson, 2009; Wuensch, 2009). For this study, the logistic regression model was deemed acceptable when the *p*-value for the model in the omnibus test of model coefficients was less than 0.10.

Hosmer and Lemeshow test

This was another absolute measure of whether the model-predicted values matched the observed values. The null hypothesis here was that there was no difference between the observed and predicted values of the criterion variable. A *p*-value for the chi-square test that was greater than 0.05 meant that the null hypothesis would not be rejected, and that the model's estimates fitted the observed data at an acceptable level (Meyers, Gamst & Guarino, 2006).

According to Garson (2009), this test was more robust than the traditional chi-square test, particularly in situations where the predictors were continuous or when the sample size was small. Garson also pointed out that while a non-significant *p*-value implied that the model-predicted values were not significantly different from the observed values, it did not mean that the model explained much of the variance in the criterion variable. Instead, the Hosmer and Lemeshow statistic implied that however much or little that the model did explain would be significant. The researcher would ensure that in the SPSS output, the *p*-value for the Hosmer and Lemeshow test should be greater than 0.05.

Classification table

Another goodness-of-fit indicator was the overall percentage of correct predictions from the classification table. The classification table was a 2x2 table which listed the number of cases where the observed values of the criterion variable were correctly predicted by the model. There had been various views regarding how large the overall percentage should be for the model to be considered 'good'. The general consensus was at least a 25% improvement over the rate of accuracy achievable by chance alone (Garson, 2009).

Hosmer and Lemeshow (2000), however, were of the view that unless classification was a stated goal of the analysis, it would be more appropriate to use the output from the classification table as a supplement to the other more rigorous goodness-of-fit measures. Hence, in Section 4.7, priority was given to the omnibus test of model coefficients and Hosmer and Lemeshow test in the evaluation of model fit.

Wald chi-square statistic

The significance of each predictor or categories of the predictor in the logistic regression model was measured using the Wald chi-square statistic. This statistic tested whether the regression coefficient for the predictor or categories of the predictor was significantly different from zero. A significant *p*-value for the Wald statistic meant that the predictor or categories of the predictor played a significant role in the prediction of the outcome defined by the criterion variable. This test was similar to the *t* test in linear regression analysis (Meyers, Gamst & Guarino, 2006).

However, one often cited weakness of the Wald statistic was that when the regression coefficient was large, the standard error would tend to become inflated. This would result in decreasing the value of the Wald statistic thereby increasing the probability of rejecting the predictor or categories of the predictor as being significant (Field, 2005; Pampel, 2000). Hence, the researcher was cautious of large values in the standard error associated with the predictor or categories of the predictor when interpreting the Wald statistic. The researcher would only recognise the predictor or categories of the predictor variable as significant when the *p*-value for the Wald statistic was less than 0.10.

4.2.3. Issues in Regression Models

In addition to model fit, there were other considerations like overfitting, sample size requirements and problems like multicollinearity which could lead to incorrect interpretations of the statistical outputs. The researcher would also be mindful of these issues in the development and examination of the logistic regression models in Section 4.7.

Overfitting

Hawkins (2004) defined the problem of overfitting as including more terms into a statistical model than were necessary or having a statistical model with too many degrees of freedom. Overfitting could produce overly optimistic model results which could be difficult to replicate with data from a different sample, and hence would raise questions regarding the usefulness of the findings. According to Babyak (2004) for a given number of cases in a data set, there would be an upper limit to the complexity of

the model that could be derived. Babyak proposed that to address the problem of overfitting, the researcher should test the model with a different data set that had been collected under different circumstances to see if the findings could be replicated.

This proposal was not feasible for this study because the respondents in the sample were not tagged, and hence it would be difficult to ensure no duplication of respondents or responses in the new data set. Instead, the researcher would look at sample size requirements to address this issue.

Sample size requirements

Researchers who used regression techniques had observed that when there were too few outcome events available relative to the number of predictor variables in the model, the following the types of errors could result:

- overfitting (Type I error) when too many variables were selected for inclusion in the final model;
- underfitting (Type II error) when significant variables were omitted from the final model; and
- paradoxical fitting (Type III error) when a variable that had a positive association with the outcome was found to have a negative association.

General guidelines had been suggested for a minimum observation-to-predictor ratio required in any regression analysis. For example, a number of researchers had recommended a minimum ratio of 10 to 1 with a minimum sample size of 100 or 50 plus a variable number that was a function of the number of predictors (Peng, Lee &

Ingersoll, 2002; Peng et al., 2002; Peduzzi et. al., 1996). The rule of thumb that was followed in this study was a ratio not less than 10 observations per predictor.

Multicollinearity

Strong correlations between one or more predictor variables in a logistic regression model would result in numerical problems known as multicollinearity. The effect of multicollinearity on the regression model could be incorrect signs and magnitudes of the regression coefficients and as a result, incorrect conclusions about the associations between the predictor and criterion variables. One suggestion to detect this problem was to review the variance inflation factor from the collinearity statistics in the SPSS output; where values above 2.5 might be a cause for concern (Maltby et al., 2008; Allison, 1999).

4.3. Description of Survey Data

The demographic and socio-economic characteristics of the respondents in the survey sample were presented in Table 4.1. The age of the respondents ranged from 20 years to 60 years with a mean of 37 years. The sample population was relatively well distributed by age, as the descriptive statistics (mean, median and standard deviation) showed that the distribution was not overly skewed in any one particular direction. As for the other continuous variable, years of investing experience, the values for this variable ranged from zero years to 37 years with a mean of 9 years. However, the distribution for this variable was slightly skewed to the right where 17.8% of the respondents, mainly from the subgroup retail investors, reported less than one year of investing experience.

Table 4.1

Demographic and Socio-economic Characteristics of Respondents

Variable	Number	Missing
Age	280 mean = 37.29 median = 37.00 std deviation = 9.28	4
Gender		0
Male	176 (62.0%)	
Female	108 (38.0%)	
Ethnicity		2
Bumiputra	85 (30.1%)	
Chinese	159 (56.4%)	
Indian	22 (7.8%)	
Other	4 (1.4%)	
Non-Malaysian	12 (4.3%)	
Education		2
School certificate	5 (1.8%)	
Undergraduate	100 (35.5%)	
Postgraduate	103 (36.5%)	
Professional qualifications	74 (26.2%)	
Monthly Household Income		12
<RM5000	39 (14.3%)	
RM5000-10000	39 (14.3%)	
RM10000-20000	78 (28.7%)	
RM20000-30000	42 (15.4%)	
>RM30000	74 (27.2%)	
Type of Investor		1
Investment professionals	75 (26.5%)	
Retail investors	208 (73.5%)	
Years of Investing Experience	269 mean = 8.76 median = 8.00 std deviation = 7.75	15

There were more male respondents (62.0%) than female respondents (38.0%) in the sample. There were also more retail investors (73.5%) than investment professionals (26.5%). The variable education was quite evenly distributed except for the category 'school certificate'. A majority of the respondents (71.3%) reported monthly household incomes larger than RM10,000, with 42.6% larger than RM20,000[21]. The variable ethnicity, however, showed an over-representation of the Chinese community in the sample (56.4%).

Based on the above observations, the predictor variables education and ethnicity were recoded as follows:

- The category 'school certificate' was reclassified as 'missing' in the variable education. This predicator variable would have three categories, i.e. 'undergraduate', 'postgraduate' and 'professional qualifications'.
- The category 'non-Malaysian' was reclassified as 'missing' and 'Indian' was combined with the category 'Other' in the variable ethnicity. This predictor variable would also have three categories, i.e. 'Bumiputra', 'Chinese' and 'Other'.

The demographic and socio-economic characteristics of the respondents in the sample by type of investor were presented in Table 4.2. Overall, the profile of the respondents by type of investor was quite similar to that for the total sample. One noticeable exception was with regard to the variable gender, where the proportion of male and female investment professionals was 70.7% and 29.3% respectively. This large proportion of males could be a characteristic of the investment services industry. The male/female distribution for the subgroup retail investors was less skewed.

[21] According to the Economic Report 2010/2011, the per capita income for Malaysia in 2009 was USD6,913 or RM23,673 at an exchange rate of RM3.4245 to USD.

Table 4.2

Demographic and Socio-economic Characteristics by Type of Investor

Variable	Investment Professionals		Retail Investors	
	Number	**Missing**	**Number**	**Missing**
Age	73 mean = 36.85 median = 36.00 std deviation = 7.87	2	206 mean = 37.50 median = 37.00 std deviation = 9.72	2
Gender				
Male	53 (70.7%)	0	122 (58.7%)	0
Female	22 (29.3%)		86 (41.3%)	
Ethnicity				
Bumiputra	19 (25.3%)	0	66 (32.0%)	2
Chinese	48 (64.0%)		110 (53.4%)	
Indian	5 (6.7%)		17 (8.3)	
Other			4 (1.9%)	
Non-Malaysian	3 (4.0%)		9 (4.4%)	
Education				
School certificate	1 (1.3%)	0	4 (1.9%)	2
Undergraduate	23 (30.7%)		77 (37.4%)	
Postgraduate	29 (38.7%)		73 (35.4%)	
Professional qualifications	22 (29.3%)		52 (25.2%)	
Monthly Household Income				
<RM5000	4 (5.6%)	3	35 (17.5%)	8
RM5000-10000	12 (16.7%)		27 (13.5%)	
RM10000-20000	25 (34.7%)		53 (26.5%)	
RM20000-30000	9 (12.5%)		33 (16.5%)	
>RM30000	22 (30.6%)		52 (26.0%)	
Years of Investing Experience	73 mean = 9.87 median = 10.00 std deviation = 6.52	2	196 mean = 8.34 median = 7.00 std deviation = 8.14	12

The other noticeable difference was with regard to the variable years of investing experience. The mean was higher for investment professionals (10 years) compared with retail investors (8 years). The shape of the curve for investment professionals was

relatively symmetrical while that for retail investors was skewed to the right, hence, the reason for the skewed distribution for the total sample.

In conclusion, the number of cases across categories in each predictor variable was large enough to conduct meaningful statistical analyses. The findings above also highlighted a weakness in snowball sampling, where the respondents would often recruit others who shared similar characteristics; in this case ethnicity.

4.4. Evidence of Prospect Theory from Survey Responses

The discussion in this section examined whether the responses from the decision scenarios in the questionnaire were consistent with the predictions of prospect theory. The behavioural biases under study and the responses received were summarised in Table 4.3. For some of the biases (framing effect, mental accounting effect, anchoring effect and status quo effect), an irrational outcome was determined from the responses from two decision scenarios tabulated in a 2x2 matrix. An irrational response for the related bias was obtained from the lower right quadrant of the 2x2 matrix, i.e. when the response for both decision scenarios was irrational (see Appendix 4.1 for details).

With the exception of the breakeven effect and mental accounting effect, all the findings in Table 4.3 were consistent with findings from existing research on prospect theory. For the behavioural biases under study, a majority of the respondents were found to have chosen the irrational outcome. For the disposition effect, even though the percentage of irrational responses was lower than 50%, it was the highest among the four response choices provided for this decision scenario. The same was observed for

the status quo effect, where the 'irrational' outcome in the 2x2 matrix had the highest number of cases.

Table 4.3

Summary of Responses from Decision Scenarios

Behavioural Bias	Irrational Response (%)	Missing Data
Framing Effect (Q1+Q2)	51.6	1
House Money Effect (Q3)	57.7	0
Snakebite Effect (Q4)	61.0	2
Breakeven Effect (Q5)	32.4	0
Mental Accounting Effect (Q6+Q7)	6.0	0
Anchoring Effect (Q8 & Q13)	56.8	4
Disposition Effect (Q9)	41.7	1
Endowment Effect (Q10+Q11)	71.4	4
Status Quo Effect (Q10+Q11 & Q12)	39.1	5

The breakeven effect was the tendency of individuals to take a gamble when presented with an opportunity to make up for losses. According to prospect theory, one element of the decision-making process was that outcomes were evaluated in terms of changes in wealth relative to a reference point (Kahneman & Tversky, 1979). Hence an explanation for the result observed could be that the 30/70 probability to breakeven in response choice (a) for question 5 might not have been compelling enough to trigger a majority of the respondents to take a gamble.

In questions 6 and 7, the scenario was to go for a play that the respondent had "waited for a long time to see". The respondents might have interpreted this phrase to mean that they should buy a ticket to see the play no matter what, and hence could have diluted the influence of the mental account effect.

On the whole, the findings supported the validity and reliability of using hypothetical decision scenarios as a tool to study decision-making behaviour. Only the mental accounting effect from questions 6 and 7 would be left out in the subsequent analyses. As for the breakeven effect, the researcher was of the view that the 92 available cases for this behavioural bias could be sufficient to conduct the intended correlation and regression analyses.

4.5. Behavioural Biases Between Investment Professionals and Retail Investors

The discussion in this section examined whether the influence of behavioural biases on decision-making behaviour varied across the subgroups investment professionals and retail investors. From Table 4.4 the chi-square test of association did not reveal any significant differences between these two subgroups for any of the behavioural biases under study, i.e. none of the *p*-values were less than 0.10.

There had been research studies with similar findings. Chen et al. (2007) analysed 46,969 individual investor brokerage accounts from a brokerage firm in China and concluded that investor sophistication did not mitigate behavioural biases nor improve trading performance. Torngren and Montgomery (2004) conducted two studies on stock market professionals and laypeople and found no difference in the stock-picking ability between these two groups. Both groups were also found to be overconfident. Baucells and Ratta (2006) conducted a survey where the sample population consisted of 261 undergraduates, Master of Business Administration (MBA) students and executives, and found that risk-taking behaviour did not vary across the three groups. Nonetheless, there were also research studies where comparisons between professional and retail investors

showed that the effect of certain behavioural biases were stronger for retail investors (Kaustia, Alho & Puttonen, 2008; Shapira & Venezia, 2001).

Table 4.4

Chi-square Test of Association Between Investment Professionals and Retail Investors

	Investment Professionals (n=75) %	Retail Investors (n=208) %	*p*-value	Odds Ratio
Framing Effect	54.7	50.7	0.558	1.171
House Money Effect	65.3	54.8	0.114	1.554
Snakebite Effect	59.5	61.8	0.719	0.905
Breakeven Effect	34.7	31.7	0.642	1.142
Anchoring Effect	57.3	56.4	0.886	1.040
Disposition Effect	44.0	41.1	0.659	1.128
Endowment Effect	68.0	72.5	0.456	0.804
Status Quo Effect	37.3	39.9	0.697	0.897

Note: % refers to the percentage of respondents who chose the 'irrational' response in the respective decision scenarios
Retail investors was the reference category for the odds ratio

While it was clear that the results presented in Table 4.4 showed no statistically significant association between decision-making behaviour and the type of investors, the odds ratio suggested that investment professionals could have been less rational for some behavioural biases. In particular, the odds ratio for the house money effect showed that investment professionals were 1.5 times more likely than retail investors to be affected by this behavioural bias. The *p*-value of 0.114, however, was outside the range of $p<0.10$ used in this study to determine statistical significance, albeit a weak one. One possible explanation for this observation could be that the work of investment professionals required them to make investment decisions as an agent, while retail investors would make investment decisions as a principal. This meant that regardless of

the outcome of the investment decision, the agent's own money would not be at risk. Hence investment professionals might be more inclined to fall under the influence of the house money effect.

This observation found some support from a study by Baucells and Ratta (2006) where it was suggested that the domain of a decision could be a factor that influenced risk-taking behaviour. The researchers found that the rates of risk-taking behaviour in professional decisions were higher compared with private decisions. However, the decisions that were tested in the study were not of a principal-agent nature.

4.6. Effect of Experience on Decision-Making Behaviour

The conclusion from the previous section was that investment professionals were just as prone to behavioural biases as retail investors. Nonetheless, the results of some behavioural finance studies suggested that such behaviour seemed to diminish with experience (Nicolosi, Peng & Zhu, 2009; Seru, Shumway & Stoffman, 2009; Krause, Wei & Yang, 2006; Weber & Welfens, 2007; List, 2004, 2003; Myagkov & Plott, 1997).

The discussion in this section focussed on the role of experience in decision-making behaviour. While Table 3.2 explained the link between each predictor variable in the survey questionnaire and the concept of experience, the analysis in this section would concentrate on the more obvious experience-related variables, namely, age, investing experience and type of investor.

Univariate logistic regression analysis was conducted and the results for the total sample were tabulated in Table 4.5. In order to facilitate the identification of patterns in the results, the biases under study were categorised into (i) decision scenarios that involved risk or loss of money, and (ii) decision scenarios that did not involve risk or loss of money. A review of the odds ratio in Table 4.5 revealed a distinct pattern that implied that biases that were related to risky choices seemed to be positively correlated with experience, while the inverse was observed for biases that were related to riskless choices.

The riskless choices were with regard to questions 10 and 11 on the endowment effect, question 12 on the status quo effect, and questions 8 and 13 on the anchoring effect. For the endowment effect, the respondents valued an asset that they owned more than a similar asset that they did not own. For the status quo effect, the respondents preferred to do nothing when presented with an option to restructure an existing portfolio. As for the anchoring effect, in question 8, the respondents' emotional assessment of a perceived loss was dependent on the 'anchor' used. And in question 13, the respondents were reluctant to factor downward trending market conditions into their decision to sell an asset. In each of these scenarios, the primary motivation was the loss of ownership rather than the element of risk or loss of money.

Age emerged as a consistent and significant predictor of decision-making behaviour both in risky (disposition effect and breakeven effect) and riskless (endowment effect and anchoring effect) choice situations. The variable investing experience only emerged as a significant predictor for the disposition effect.

Table 4.5

Influence of Experience on Finance-Related Decision Behaviour - Total Sample

	Number	Waldχ^2	*p*-value	Odds Ratio
Decision scenarios that involved risk or loss of money				
Disposition Effect				
Age	279	5.448	0.020*	1.032
Investing experience	268	5.516	0.019*	1.039
Type of investor	282	0.195	0.659	1.128
House Money Effect				
Age	280	0.000	0.996	1.000
Investing experience	269	0.538	0.463	1.012
Type of investor	283	2.482	0.115	1.554
Snakebite Effect				
Age	278	2.001	0.157	1.019
Investing experience	267	2.596	0.107	1.027
Type of investor	281	0.130	0.719	0.905
Breakeven Effect				
Age	280	3.033	0.082*	1.024
Investing experience	269	0.783	0.376	1.015
Type of investor	283	0.216	0.642	1.142
Framing Effect				
Age	279	0.011	0.918	0.999
Investing experience	268	0.036	0.849	1.003
Type of investor	282	0.342	0.558	1.171
Decision scenarios that did not involve risk or loss of money				
Endowment Effect				
Age	276	6.236	0.013*	0.964
Investing experience	266	0.988	0.320	0.983
Type of investor	279	0.554	0.457	0.804
Status Quo Effect				
Age	275	0.346	0.557	0.992
Investing experience	265	1.272	0.259	0.981
Type of investor	278	0.151	0.697	0.897
Anchoring Effect				
Age	276	5.053	0.025*	0.970
Investing experience	266	0.657	0.418	0.987
Type of investor	279	0.021	0.886	1.040

Note * Significant at $p<0.10$

For the predictor variable 'type of investor' retail investors was the reference category for the odds ratio

The univariate logistic regression analysis was repeated for the subgroups investment professionals and retail investors, and the results tabulated in Tables 4.6 and 4.7 respectively. In Table 4.6, the pattern in the odds ratio for the subgroup investment professionals was similar to that for the total sample. One exception was with regard to the breakeven effect, where the odds ratio showed a negative correlation with the experience-related variables age and investing experience. As for the relevance of the experience-related variables in predicting irrational decision-making behaviour, the *p*-values for age in the endowment effect and investing experience in the status quo effect were between 0.05 and 0.10, which implied weak statistical significance.

In Table 4.7, the observations from the analysis of the total sample were mirrored in the subgroup retail investors. This was expected as the number of cases in this subgroup, which was three times that for the subgroup investment professionals, would have a considerable affect on the findings for the total sample.

The discussion in Section 2.6 showed that the results of studies conducted on the effect of experience or investor sophistication on behavioural biases were mixed. The results from the statistical analyses in this section might provide some insight to results of these previous studies. The pattern in the odds ratio in Tables 4.5, 4.6 and 4.7 implied that the role of experience in tempering loss aversion behaviour could be more relevant for decisions that involved riskless choice. This was consistent with the findings from experiments conducted by List (2004, 2003) on the endowment effect, but were inconsistent with the findings from similar studies on the disposition effect (Seru, Shumway & Stoffman, 2009; Krause, Wei & Yang, 2006; Weber & Welfens, 2007). The inconsistency in the finding for the disposition effect could be due to the approach taken by the respective studies to measure the effect. Seru, Sumway and Stoffman

(2009) used a modelling approach, Krause, Wei and Yang (2006) analysed trading strategies and trade durations, and Weber and Welfens (2007) conducted laboratory experiments. In this study, the respondents were presented with a scenario that described the disposition effect and were required to choose a response from four given options.

Table 4.6

Influence of Experience on Finance-Related Decision Behaviour - Subgroup Investment Professionals

	Number	Waldχ^2	*p*-value	Odds Ratio
Decision scenarios that involved risk or loss of money				
Disposition Effect				
Age	73	0.751	0.386	1.027
Investing experience	73	0.065	0.799	0.991
House Money Effect				
Age	73	0.210	0.647	1.015
Investing experience	73	0.056	0.812	1.009
Snakebite Effect				
Age	72	0.087	0.768	0.991
Investing experience	72	0.021	0.886	1.005
Breakeven Effect				
Age	73	0.876	0.349	0.970
Investing experience	73	0.336	0.562	0.978
Framing Effect				
Age	73	0.530	0.467	1.023
Investing experience	73	0.073	0.780	1.010
Decision scenarios that did not involve risk or loss of money				
Endowment Effect				
Age	73	2.869	0.090*	0.946
Investing experience	73	0.972	0.324	0.963
Status Quo Effect				
Age	73	1.507	0.220	0.961
Investing experience	73	3.427	0.064*	0.927
Anchoring Effect				
Age	73	0.317	0.574	0.983
Investing experience	73	0.059	0.809	1.009

Note * Significant at $p<0.10$

Table 4.7

Influence of Experience on Finance-Related Decision Behaviour - Subgroup Retail Investors

	Number	Waldχ^2	*p*-value	Odds Ratio
Decision scenarios that involved risk or loss of money				
Disposition Effect				
Age	205	4.517	0.034*	1.033
Investing experience	195	7.367	0.007*	1.052
House Money Effect				
Age	206	0.004	0.948	0.999
Investing experience	196	0.302	0.583	1.010
Snakebite Effect				
Age	205	2.544	0.111	1.024
Investing experience	195	3.192	0.074*	1.035
Breakeven Effect				
Age	206	5.568	0.018*	1.038
Investing experience	196	1.519	0.218	1.023
Framing Effect				
Age	205	0.280	0.596	0.992
Investing experience	195	0.002	0.966	1.001
Decision scenarios that did not involve risk or loss of money				
Endowment Effect				
Age	202	3.685	0.055*	0.969
Investing experience	193	0.319	0.572	0.989
Status Quo Effect				
Age	201	0.019	0.889	0.998
Investing experience	192	0.091	0.763	0.995
Anchoring Effect				
Age	202	4.588	0.032*	0.968
Investing experience	193	1.145	0.285	0.981

Note * Significant at $p<0.10$

In the studies cited, the behaviour under examination was in relation to either a riskless choice (endowment effect) or a risky choice (disposition effect). The researcher found only one study where the participants were exposed to tasks that involved both riskless and risky choices. The participants in the study by Gachter, Johnson and Herrmann

(2007) were 660 randomly selected customers from a German car manufacturer. The riskless choice task was an endowment effect experiment, while the risky choice task consisted of six lotteries with a 50-50 chance of a fixed gain of €6 and losses that varied from €2 to €7. The authors found no difference in loss aversion behaviour for both the riskless and risky choice tasks; and that loss aversion increased with age, income and wealth but decreased with education.

The difference in the results, particularly with respect to riskless choice tasks, could be due to the choice of research participants. Gachter, Johnson and Herrmann (2007) selected consumers for their dissimilar socio-demographic backgrounds in order to study the effect of these variables on loss aversion. In contrast, this study targeted respondents who either had investing experience or had knowledge or exposure to financial and investment matters. Nonetheless, the finding in this section provided some evidence that while loss aversion behaviour existed in both riskless and risky choice tasks, whether or not investors could learn to overcome their behavioural biases would depend on the nature of the choice task.

4.7. Effect of Investor Characteristics on Decision-Making Behaviour

It was highlighted in Section 3.4.2 that the predictor variables selected for the survey questionnaire to assess financial decision-making behaviour were also used by financial advisors to assess the risk tolerance of investors. The association between these variables and risk tolerance was summarised in Table 3.2. The aim of this section, therefore, was to examine whether any of the predictor variables, taken alone or together with other variables, would emerge as significant predictors of financial decision-making behaviour. The discussions that follow would be based on the results

of chi-square tests and multivariate logistic regression analyses on the total sample and the two categories of investors.

The logistic regression model-building approach was outlined in Section 4.2.1. Only biases (criterion variables) with multivariate logistic regression models that passed the omnibus test of model coefficients and Hosmer and Lemeshow goodness-of-fit test was presented and discussed.

4.7.1. Total Sample

Chi-square tests were conducted on the total sample to examine the relationship between the demographic and socio-economic characteristics of the respondent and behavioural biases under study. From the results which were tabulated in Table 4.8, significant predictors were observed for the breakeven effect, house money effect and framing effect.

- For the breakeven effect, the significant predictors were gender, ethnicity and asset size.
- For the house money effect, the significant predictors were gender and monthly household income.
- For the framing effect, only monthly household income emerged as a significant predictor.

Table 4.8

Effect of Demographic and Socio-Economic Variables on Irrational Decision-Making Behaviour – Total Sample

Variables	Disposition			Breakeven			House Money			Framing			Endowment			Status Quo			Anchoring		
	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*
Gender			0.452			0.009*			0.005*			0.659			0.412			0.996			0.344
Male	43.4	(175)		38.1	(176)		64.2	(176)		50.6	(176)		69.7	(175)		39.1	(174)		54.6	(174)	
Female	38.9	(108)		23.1	(108)		47.2	(108)		53.3	(107)		74.3	(105)		39.0	(105)		60.4	(106)	
Ethnicity			0.645			0.007*			0.463			0.721			0.419			0.611			0.241
Bumiputra	36.5	(85)		18.8	(85)		57.6	(85)		51.8	(85)		73.5	(83)		42.7	(82)		50.6	(83)	
Chinese	42.1	(159)		38.4	(159)		59.1	(159)		49.4	(158)		71.5	(158)		38.6	(158)		58.9	(158)	
Others	44.0	(25)		34.6	(26)		46.2	(26)		57.7	(26)		60.0	(25)		32.0	(25)		68.0	(25)	
Education			0.154			0.754			0.667			0.778			0.900			0.659			0.527
Undergraduate	36.0	(100)		29.0	(100)		54.0	(100)		55.0	(100)		71.0	(100)		43.0	(100)		53.0	(100)	
Postgraduate	41.7	(103)		33.0	(103)		57.3	(103)		50.5	(103)		70.6	(102)		39.6	(101)		58.8	(102)	
Professional	50.7	(73)		33.8	(74)		60.8	(74)		50.7	(73)		73.6	(72)		36.1	(72)		61.1	(72)	
Income			0.107			0.334			0.020*			0.022*			0.489			0.737			0.469
<RM5000	35.9	(39)		30.8	(39)		69.2	(39)		48.7	(39)		70.3	(37)		43.2	(37)		60.5	(38)	
RM5000-10000	43.6	(39)		23.1	(39)		41.0	(39)		35.9	(39)		71.8	(39)		42.1	(38)		65.8	(38)	
RM10000-20000	33.3	(78)		32.1	(78)		69.2	(78)		57.7	(78)		63.6	(77)		32.5	(77)		58.4	(77)	
RM20000-30000	39.0	(41)		31.0	(42)		54.8	(42)		40.5	(42)		78.0	(41)		41.5	(41)		56.1	(41)	
>RM30000	54.1	(74)		41.9	(74)		52.7	(74)		63.5	(74)		74.3	(74)		40.5	(74)		48.6	(74)	
Asset size			0.954			0.022*			0.533			0.447			0.539			0.282			0.495
Size1	41.3	(63)		25.4	(63)		55.6	(63)		54.0	(63)		71.4	(63)		46.0	(63)		65.1	(63)	
Size2	35.0	(40)		52.5	(40)		70.0	(40)		37.5	(40)		72.5	(40)		27.5	(40)		55.0	(40)	
Size3	41.2	(34)		23.5	(34)		55.9	(34)		55.9	(34)		57.6	(33)		33.3	(33)		60.6	(33)	
Size4	37.5	(24)		29.2	(24)		62.5	(24)		54.2	(24)		70.8	(24)		29.2	(24)		62.5	(24)	
Size5	42.1	(76)		26.0	(77)		54.5	(77)		53.2	(77)		73.7	(76)		41.3	(75)		50.7	(75)	

Note: * Significant at $p<0.10$

% refers to the percentage of respondents who chose the 'irrational' response in the respective decision scenarios

Definition of asset size:

For investment professionals – Size1 (<RM100 million), Size2 (RM100-RM399 million), Size3 (RM400-RM699 million), Size4 (RM700-RM999 million), Size5 (>RM1 billion)

For retail investors – Size1 (<RM250,000), Size2 (RM250,000-RM499,000), Size3 (RM500,000-RM999,000), Size4 (RMRM1,000,000-RM1,999,000), Size5 (>RM2 million)

No significant predictors were observed for the status quo effect[22]. In summary, from Tables 4.5 and 4.8, predictors that emerged as statistically significant in more than one behavioural bias were age, gender and monthly household income. The discussions that follow would be with regard to multivariate logistic regression models for the breakeven effect, house money effect and endowment effect, as these were the only ones that passed the model-fitting tests.

The regression model for the breakeven effect presented in Table 4.9, consisted of three two-way interaction terms. According to Jaccard (2001) an interaction effect was one where the effect of the predictor variable on the criterion variable was dependent on a third variable known as a moderator. The variable age emerged as the common moderator for all three interaction terms. Furthermore, all three interaction terms were statically significant with *p*-values that were less than 0.05. Holding all other factors constant, the following observations were made.

- Age by gender interaction: Irrational responses were positively associated with age, and were higher for male respondents. With every additional year, the likelihood of a male respondent over a female respondent to choose an irrational response would increase by 1.020 times.
- Age by ethnicity interaction: Given the same age, Chinese respondents were 1.031 times more likely to be affected by the breakeven effect compared with Bumiputra respondents. The interaction term also implied that the 'irrational' tendency of Chinese respondents over Bumiputra respondents would widen with increasing age.
- Age by networth/portfolio size interaction: There was only one category of the variable that had a *p*-value of less than 0.05, i.e. retail investors with reported

[22] In Table 4.5, age was a significant predictor of the disposition effect, breakeven effect, endowment effect and anchoring effect; while investing experience was a significant predictor of the disposition effect.

networth between RM250,000-RM499,000 and investments professionals who managed portfolios between RM100 million-RM399 million in size. The odds ratio of 1.037 implied that this category of respondents were more willing than the reference category to take on additional risk to recover a loss. However, there was no distinct pattern in the odds ratio for the four categories of the variable.

Table 4.9

Results of a Multivariate Logistic Regression Model for the Breakeven Effect – Total Sample

Predictor	β	**SE**	**Waldχ^2**	***p*-value**	**Odds Ratio**
Age*Gender	0.019	0.008	5.631	0.018 *	1.020
Age*Ethnicity			11.193	0.004 *	
Age*Chinese	0.030	0.009	11.192	0.001 *	1.031
Age*Other	0.018	0.013	2.123	0.145	1.018
Age*Asset Size			11.867	0.018 *	
Age*Size1	0.011	0.012	0.805	0.370	1.011
Age*Size2	0.037	0.012	10.055	0.002 *	1.037
Age*Size3	-0.002	0.012	0.026	0.872	0.998
Age*Size4	0.008	0.013	0.374	0.541	1.008
Constant	-2.527	0.429	34.657	0.000	0.080

Test	χ^2	***df***	***p*-value**
Omnibus test of model coefficients	31.925	7	<0.000*
Hosmer & Lemeshow goodness-of-fit test	7.687	8	0.465

Note * Significant at $p<0.10$

Definition of asset size:

For investment professionals – Size1 (<RM100 million), Size2 (RM100-RM399 million), Size3 (RM400-RM699 million), Size4 (RM700-RM999 million)

For retail investors – Size1 (<RM250,000), Size2 (RM250,000-RM499,000), Size3 (RM500,000-RM999,000), Size4 (RMRM1,000,000-RM1,999,000)

Reference category for gender – female

Reference category for ethnicity – Bumiputra

Reference category for asset size – >RM1 billion for investment professionals and >RM2 million for retail 0069nvestors

In summary, the results of the regression model for the breakeven effect implied that ethnic Chinese male respondents were more likely to be affected by this behavioural bias, and that this likelihood could increase with age. The role of the variable networth/portfolio size was less obvious.

The regression model for the house money effect was presented in Table 4.10. The variables in the equation were gender, monthly household income and a two-way interaction term between ethnicity and type of investor. It was observed that ethnicity and type of investor were not significant predictors in the chi-square test (Table 4.8) and univariate logistic regression analysis (Table 4.5) respectively, but became significant in an interaction term. Holding all other factors constant, the following observations were made.

- Males were 1.836 times more likely than females to choose an irrational response.
- Respondents with monthly household income <RM5,000 were 2.538 times more likely than respondents with monthly household income of >RM30,000 (reference category) to choose an irrational response. Similarly respondents with monthly household income of between RM10,000-RM20,000 were 2.041 times more likely than the reference category to choose an irrational response. Even though there was no distinct pattern in the odds ratio for the four categories of the variable, of the two categories of the variable with highly significant *p*-values, the odds ratio for the latter was slightly lower than for the former.
- Type of investor by ethnicity interaction: Given the same type of investor, Chinese respondents were 2.472 times more likely than Bumiputra respondents to choose an irrational response. Alternatively, given the same ethnic type,

investment professionals were 2.472 times more likely than retail investors to choose an irrational response.

Table 4.10

Results of a Multivariate Logistic Regression Model for the House Money Effect – Total Sample

Predictor	β	**SE**	**Waldχ^2**	***p*-value**	**Odds Ratio**
Gender	0.608	0.280	4.722	0.030*	1.836
Income			11.132	0.025*	
<RM5k	0.931	0.442	4.442	0.035*	2.538
RM5k-10k	-0.331	0.423	0.614	0.433	0.718
RM10k-20k	0.714	0.354	4.060	0.044*	2.041
RM20k-30k	0.043	0.415	0.011	0.916	1.044
Type investor*Ethnicity			5.766	0.056*	
Professional*Chinese	0.905	0.378	5.738	0.017*	2.472
Professional*Other	-0.005	0.945	0.000	0.996	0.995
Constant	-0.478	0.316	2.295	0.130	0.620
Test			**χ^2**	***df***	***p*-value**
Omnibus test of model coefficients			22.674	7	0.002*
Hosmer & Lemeshow goodness-of-fit test			3.304	8	0.914

Note * Significant at $p<0.10$
Reference category for gender - female
Reference category for income – >RM30,000
Reference category for ethnicity – Bumiputra

In summary, the results of the regression model for the house money effect implied that male respondents were more likely to be affected by this behavioural bias, and that this tendency decreased marginally with increasing monthly household income. Furthermore, investment professionals who were ethnic Chinese were more willing to risk the 'house's' money when such an opportunity presented itself.

The regression model for the endowment effect was presented in Table 4.11. The variables in the equation were age and a two-way interaction term between monthly

household income and age. It was observed that monthly household income was not a significant predictor in the chi-square test (Table 4.8), but became significant in an interaction term. Holding all other factors constant, the following observations were made.

- The likelihood of an irrational response was negatively related to the age of the respondent. With every additional year, the likelihood of the respondent to choose an irrational response would decrease by a factor of 0.039.
- Age by monthly household income interaction: Given the same age, respondents with monthly household income <RM5,000 and between RM10,000-RM20,000 were 0.028 times and 0.020 times respectively less likely than respondents with monthly household income of >RM30,000 to choose an irrational response. Once again there was no distinct pattern in the odds ratio for the categories of the variable.

Table 4.11

Results of a Multivariate Logistic Regression Model for the Endowment Effect – Total Sample

Predictor	β	**SE**	**Wald**χ^2	***p*-value**	**Odds Ratio**
Age	-0.040	0.016	5.896	0.015*	0.961
Age*Income			8.189	0.085*	
Age*<RM5k	-0.028	0.015	3.376	0.066*	0.972
Age*RM5k-10k	-0.012	0.012	0.992	0.319	0.988
Age*RM10k-20k	-0.020	0.009	5.096	0.024*	0.980
Age*RM20k-30k	0.002	0.011	0.042	0.838	1.002
Constant	2.807	0.675	17.317	0.000	16.564
Test			χ^2	***df***	***p*-value**
Omnibus test of model coefficients			13.632	5	0.018*
Hosmer & Lemeshow goodness-of-fit test			3.676	8	0.885

Note * Significant at $p<0.10$
Reference category for income – >RM30,000

In summary, the results of the regression model for the endowment effect implied that age was a significant predictor both on its own and as a moderator for monthly household income. The odds ratio suggested that both the variable age and the interaction term (age and monthly household income) were negatively correlated with this behavioural bias.

The results from the multivariate logistic regression analysis for the breakeven effect, house money effect and endowment effect on the total sample lent support to the findings in section 4.6., i.e. the effect of demographic and socio-economic variables on decision-making behaviour of investors were dependent on whether the decision was one that involved a riskless or risky choice. The coefficients for the regression models were generally positive for the breakeven effect and house money effect, but were negative for the endowment effect. The results also drew attention to the variables gender and ethnicity as significant predictors of financial decision-making behaviour; where male and ethnic Chinese respondents were found to be more prone to behavioural biases.

As discussed in Chapter 2, of the studies that examined the link between gender and behavioural finance biases, the most cited was the study by Barber and Odean (2001) that concluded that men tend to be more overconfident and the subsequent excessive trading behaviour led to poorer returns. In another study by Da Costa Jr, Mineto and Da Silva (2008), the authors found that women were more inclined not to hold on to losing stocks, were therefore less disposed to the disposition effect. On matters concerning financial decision-making, women had been stereotyped as being more risk-averse than men (Eckel & Grossman, 2008; Schubert et.al., 1999).

Cultural differences also exist in financial and economic decision-making behaviour. Nisbett et al. (2001), in their review suggested that the cognitive processes of East Asians were more holistic whereas Westerners were more analytic. This observation was confirmed by a study conducted by Levinson and Peng (2007) that involved subjects from the United States and China. Another study by Sowinski, Schnusenberg and Materne (2010) on the responses to behavioural biases between students in Germany and the United States found the German sample markedly less biased.

4.7.2. Subgroup Investment Professionals

Chi-square tests were conducted on the subgroup investment professionals to examine the relationship between respondent characteristics and the behavioural biases under study. From the results which were tabulated in Table 4.12, significant predictors were observed for the disposition effect, breakeven effect and framing effect.

- For the disposition effect, gender, education and monthly household income emerged as significant predictors.
- For the breakeven effect, the predictor variables ethnicity and monthly household income had *p*-values less than 0.05.
- For the framing effect, monthly household income was the only significant predictor.

No significant predictors were observed for the house money effect and anchoring effect.[23] In summary, from Tables 4.6 and 4.12, only one predictor emerged as

[23] In Table 4.6, age and investing experience were significant predictors of the endowment effect and status quo effect respectively.

Table 4.12

Effect of Demographic and Socio-Economic Variables on Irrational Decision-Making Behaviour – Investment Professionals

Variables	Disposition			Breakeven			House Money			Framing			Endowment			Status Quo			Anchoring		
	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*
Gender			0.090*			0.386			0.464			0.620			0.572			0.525			0.753
Male	37.7	(53)		37.7	(53)		67.9	(53)		52.8	(53)		66.0	(53)		39.6	(53)		58.5	(53)	
Female	59.1	(22)		27.3	(22)		59.1	(22)		59.1	(22)		72.7	(22)		31.8	(22)		54.5	(22)	
Ethnicity			0.388			0.027*			0.136			0.324			0.212			0.585			0.130
Bumiputra	57.9	(19)		10.5	(19)		47.4	(19)		63.2	(19)		57.9	(19)		26.3	(19)		52.6	(19)	
Chinese	39.6	(48)		43.8	(48)		72.9	(48)		50.0	(48)		72.9	(48)		39.6	(48)		54.2	(48)	
Others	40.0	(5)		20.0	(5)		60.0	(5)		80.0	(5)		40.0	(5)		40.0	(5)		100	(5)	
Education			0.040*			0.211			0.873			0.894			0.951			0.885			0.364
Undergraduate	26.1	(23)		21.7	(23)		60.9	(23)		52.2	(23)		69.6	(23)		39.1	(23)		56.5	(23)	
Postgraduate	44.8	(29)		44.8	(29)		65.5	(29)		58.6	(29)		65.5	(29)		34.5	(29)		48.3	(29)	
Professional	63.6	(22)		31.8	(22)		68.2	(22)		54.5	(22)		68.2	(22)		40.9	(22)		68.2	(22)	
Income			0.051*			0.011*			0.557			0.028*			0.128			0.582			0.495
<RM5000	0	(4)		75.0	(4)		50.0	(4)		25.0	(4)		100	(4)		50.0	(4)		50.0	(4)	
RM5000-10000	58.3	(12)		8.3	(12)		50.0	(12)		41.7	(12)		66.7	(12)		41.7	(12)		66.7	(12)	
RM10000-20000	32.0	(25)		28.0	(25)		76.0	(25)		76.0	(25)		72.0	(25)		28.0	(25)		60.0	(25)	
RM20000-30000	33.3	(9)		22.2	(9)		66.7	(9)		22.2	(9)		88.9	(9)		55.6	(9)		77.8	(9)	
>RM30000	63.6	(22)		59.1	(22)		68.2	(22)		59.1	(22)		50.0	(22)		31.8	(22)		45.5	(22)	
Portfolio size			0.806			0.215			0.632			0.301			0.820			0.800			0.672
<RM100mn	30.8	(13)		7.7	(13)		76.9	(13)		69.2	(13)		69.2	(13)		38.5	(13)		53.8	(13)	
RM100mn-1bn	33.3	(15)		33.3	(15)		60.0	(15)		40.0	(15)		73.3	(15)		26.7	(15)		66.7	(15)	
>RM1bn	40.9	(22)		31.8	(22)		68.2	(22)		54.5	(22)		63.6	(22)		31.8	(22)		68.2	(22)	

Note: * Significant at $p<0.10$

% refers to the percentage of respondents who chose the 'irrational' response in the respective decision scenarios

statistically significant in more than one behavioural bias, which was monthly household income. The discussions that follow would be with regard to multivariate logistic regression models for the disposition effect and breakeven effect, as these were the only ones that passed the model-fitting tests.

The regression model for the disposition effect was presented in Table 4.13. The variables in the equation were education, monthly household income and gender. Holding all other factors constant, the following conclusions were drawn.

- The *p*-values indicated that the variable education was a highly significant predictor of the disposition effect. Even though the coefficients for the categories of the variable were negative, the pattern in the odds ratio implied that the likelihood of choosing an irrational response was significantly higher for respondents with professional qualifications.
- The variable monthly household income was also negatively correlated with the disposition effect. Only one category of the variable was significant, i.e. respondents with monthly household income of between RM10,000-RM20,000 were 0.838 times less likely than the reference category to choose an irrational response. There was no distinct pattern in the odds ratio.
- Males were 0.696 times less likely than females to choose an irrational response.

In summary, the results from regression model for the disposition effect implied that within the subgroup investment professionals, females and respondents with professional qualifications would be more likely to be affected by this behavioural bias. The influence of monthly household income was less obvious.

Table 4.13

Results of a Multivariate Logistic Regression Model for the Disposition Effect – Investment Professionals

Predictor	β	**SE**	**Wald**χ^2	***p*-value**	**Odds Ratio**
Education			7.874	0.020*	
Undergraduate	-2.264	0.823	7.517	0.006*	0.104
Postgraduate	-1.418	0.702	4.082	0.043*	0.242
Income			6.704	0.152	
<RM5k	-7.910	29.871	0.070	0.791	0.000
RM5k-10k	-0.568	0.830	0.468	0.494	0.567
RM10k-20k	-1.822	0.734	6.168	0.013*	0.162
RM20k-30k	-1.272	0.926	1.889	0.169	0.280
Gender	-1.192	0.664	3.226	0.072*	0.304
Constant	2.901	0.962	9.092	0.003	18.188

Test	χ^2	***df***	***p*-value**
Omnibus test of model coefficients	23.371	7	0.001*
Hosmer & Lemeshow goodness-of-fit test	8.353	7	0.303

Note * Significant at $p<0.10$
Reference category for education – professional qualifications
Reference category for income – >RM30,000
Reference category for gender - female

The regression model for the breakeven effect was presented in Table 4.14. The variables in the equation were monthly household income and ethnicity. Holding all other factors constant, the following conclusions were drawn.

- The odds ratio implied that respondents with monthly household income RM5,000 and above were less likely than the reference category (>RM30,000) to choose an irrational response. However, this relationship was statistically significant (*p*-value of less than 0.05) only for respondents with monthly household income RM5,000-RM10,000.
- Chinese respondents were 8.253 times more likely to choose an irrational response than Bumiputra respondents.

Table 4.14

Results of a Multivariate Logistic Regression Model for the Breakeven Effect – Investment Professionals

Predictor	β	**SE**	**Wald**χ^2	***p*-value**	**Odds Ratio**
Income			10.614	0.031*	
<RM5k	0.974	1.390	0.490	0.484	2.647
RM5k-10k	-2.851	1.175	5.882	0.015*	0.058
RM10k-20k	-1.204	0.681	3.127	0.077*	0.300
RM20k-30k	-2.314	1.209	3.666	0.056*	0.099
Ethnicity			6.614	0.037*	
Chinese	2.111	0.883	5.711	0.017*	8.253
Other	0.622	1.435	0.188	0.665	1.863
Constant	-1.280	0.883	2.099	0.147	0.278

Test	χ^2	***df***	***p*-value**
Omnibus test of model coefficients	22.130	6	0.001*
Hosmer & Lemeshow goodness-of-fit test	1.358	6	0.968

Note * Significant at $p<0.10$
Reference category for income – >RM30,000
Reference category for ethnicity - Bumiputra

In summary, the results from the regression model for the breakeven effect reinforced the finding that ethnicity was a predictor of decision-making behaviour; where Chinese respondents in general (Table 4.9) and Chinese investment professionals in particular, exhibited a greater tendency to yield to the influence of the breakeven effect. The results also implied that the tendency to exhibit breakeven behaviour might be linked to an income threshold, above which the respondent would likely take a gamble to recover losses. From the results, the threshold could be any amount greater than RM30,000 per month.

4.7.3. Subgroup Retail Investors

Chi-square tests were conducted on the subgroup retail investors to examine the relationship between respondent characteristics and the behavioural biases under study. From the results which were tabulated in Table 4.15, significant predictors were observed for the disposition effect, breakeven effect, house money effect, framing effect and endowment effect.

- For the disposition effect, gender emerged as a significant predictor.
- For the breakeven effect, predictor variables with *p*-values less than 0.10 were gender, ethnicity and asset size.
- For the house money effect, gender and monthly household income had *p*-values less than 0.05.
- For the framing effect, monthly household income was the only significant predictor.
- For the endowment effect monthly household income was a significant predictor.

No significant predictors were observed for the status quo effect.[24] In summary, from Tables 4.7 and 4.15, predictors that emerged as statistically significant in more than one behavioural bias were age, gender and monthly household income; similar to the findings for the total sample. The discussions that follow would be with regard to multivariate logistic regression models for the breakeven effect, house money effect and endowment effect, as these were the only ones that passed the model-fitting tests.

[24] In Table 4.7, age was a significant predictor of the anchoring effect.

Table 4.15

Effect of Demographic and Socio-Economic Variables on Irrational Decision-Making Behaviour – Retail Investors

Variables	Disposition			Breakeven			House Money			Framing			Endowment			Status Quo			Anchoring		
	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*	%	(n)	*p*
Gender			0.070*			0.012*			0.010*			0.803			0.569			0.455			0.183
Male	46.3	(121)		38.5	(122)		62.3	(122)		50.0	(122)		71.1	(121)		39.2	(120)		52.5	(120)	
Female	33.7	(86)		22.1	(86)		44.2	(86)		51.8	(85)		74.7	(83)		41.0	(83)		61.9	(84)	
Ethnicity			0.185			0.088*			0.321			0.953			0.413			0.299			0.384
Bumiputra	30.3	(66)		21.2	(66)		60.6	(66)		48.5	(66)		78.1	(64)		47.6	(63)		50.0	(64)	
Chinese	43.6	(110)		36.4	(110)		52.7	(110)		49.5	(109)		70.6	(109)		38.5	(109)		60.6	(109)	
Others	45.0	(20)		38.1	(21)		42.9	(21)		52.4	(21)		65.0	(20)		30.0	(20)		60.0	(20)	
Education			0.787			0.785			0.808			0.585			0.842			0.503			0.426
Undergraduate	39.0	(77)		31.2	(77)		51.9	(77)		55.8	(77)		71.4	(77)		44.2	(77)		51.9	(77)	
Postgraduate	41.1	(73)		28.8	(73)		53.4	(73)		47.9	(73)		72.2	(72)		42.3	(71)		62.5	(72)	
Professional	45.1	(51)		34.6	(52)		57.7	(52)		49.0	(51)		76.0	(50)		34.0	(50)		58.0	(50)	
Income			0.555			0.911			0.019*			0.086*			0.069*			0.872			0.613
<RM5000	40.0	(35)		25.7	(35)		71.4	(35)		51.4	(35)		66.7	(33)		42.4	(33)		61.8	(34)	
RM5000-10000	37.0	(27)		29.6	(27)		37.0	(27)		33.3	(27)		74.1	(27)		42.3	(26)		65.4	(26)	
RM10000-20000	34.0	(53)		34.0	(53)		66.0	(53)		49.1	(53)		59.6	(52)		34.6	(52)		57.7	(52)	
RM20000-30000	40.6	(32)		33.3	(33)		51.5	(33)		45.5	(33)		75.0	(32)		37.5	(32)		50.0	(32)	
>RM30000	50.0	(52)		34.6	(52)		46.2	(52)		65.4	(52)		84.6	(52)		44.2	(52)		50.0	(52)	
Networth			0.840			0.041*			0.186			0.658			0.583			0.170			0.133
<RM0.25mn	44.0	(50)		30.0	(50)		50.0	(50)		50.0	(50)		72.0	(50)		48.0	(50)		68.0	(50)	
RM0.25mn-0.5mn	32.3	(31)		54.8	(31)		74.2	(31)		38.7	(31)		67.7	(31)		25.8	(31)		51.6	(31)	
RM0.5mn-1mn	44.8	(29)		27.6	(29)		55.2	(29)		55.2	(29)		60.7	(28)		39.3	(28)		60.7	(28)	
RM1mn-2mn	39.1	(23)		26.1	(23)		60.9	(23)		56.5	(23)		69.6	(23)		26.1	(23)		60.9	(23)	
>RM2mn	42.6	(54)		23.6	(55)		49.1	(55)		52.7	(55)		77.8	(54)		45.3	(53)		43.4	(53)	

Note: * Significant at $p<0.10$

% refers to the percentage of respondents who chose the 'irrational' response in the respective decision scenarios

The regression model for the breakeven effect presented in Table 4.16, consisted of three two-way interaction terms. For all three interaction terms, the variables gender, ethnicity and asset size were moderated by age, and were statically significant with *p*-values that were less than 0.05. The results here were similar to the multivariate regression model for the total sample (Table 4.9). Holding all other factors constant, the following conclusions were drawn.

- The likelihood of an irrational response was positively correlated with the age of the respondent.
- Given the same age:
    - Male respondents were 1.023 times more likely to take the risk to breakeven on a loss compared with a female respondent.
    - Chinese respondents were 1.031 times more likely to be affected by the breakeven effect compared with Bumiputra respondents.
    - Retail investors with reported networth between RM250,000-RM499,000 were 1.041 times more likely than the reference category to choose an irrational response.

In summary, the results for the regression model for the breakeven effect for retail investors mirrored that for the total sample. Ethnic Chinese male respondents were more likely to be affected by this behavioural bias, and that this likelihood could increase with age.

Table 4.16

Results of a Multivariate Logistic Regression Model for the Breakeven Effect – Retail Investors

Predictor	β	**SE**	**Waldχ^2**	***p*-value**	**Odds Ratio**
Age*Gender	0.023	0.009	6.244	0.012 *	1.023
Age*Ethnicity			9.086	0.011 *	
Age*Chinese	0.031	0.010	9.011	0.003 *	1.031
Age*Other	0.021	0.013	2.476	0.116	1.021
Age*Asset Size			10.949	0.027 *	
Age*<RM0.25mn	0.024	0.014	2.836	0.092 *	1.024
Age*RM0.25mn-0.50mn	0.040	0.014	8.736	0.003 *	1.041
Age*RM0.50mn-1mn	0.002	0.013	0.013	0.909	1.002
Age*RM1mn-2mn	0.006	0.015	0.159	0.690	1.006
Constant	-2.715	0.498	29.728	0.000	0.006
Test			**χ^2**	***df***	***p*-value**
Omnibus test of model coefficients			29.791	7	<0.000*
Hosmer & Lemeshow goodness-of-fit test			5.702	8	0.681

Note * Significant at $p<0.10$
Reference category for gender – female
Reference category for ethnicity – Bumiputra
Reference category for asset size – >RM2 million

The regression model for the house money effect was presented in Table 4.17. The variables in the equation were gender and monthly household income. Once again the results here were similar to the multivariate regression model for the total sample (Table 4.10). Holding all other factors constant, the following conclusions were drawn.

- Males were 2.238 times more likely than females to choose an irrational response.
- Respondents with monthly household income <RM5,000 were 3.914 times more likely than the reference category to choose an irrational response.
- Respondents with monthly household income of between RM10,000-20,000 were 2.397 times more likely than the reference category to choose an irrational response.

Table 4.17

Results of a Multivariate Logistic Regression Model for the House Money Effect – Retail Investors

Predictor	β	**SE**	**Waldχ^2**	***p*-value**	**Odds Ratio**
Gender	0.806	0.318	6.441	0.011*	2.238
Income			12.388	0.015*	
<RM5k	1.365	0.492	7.692	0.006*	3.914
RM5k-10k	-0.142	0.503	0.079	0.778	0.868
RM10k-20k	0.874	0.410	4.549	0.033*	2.397
RM20k-30k	0.284	0.455	0.389	0.533	1.328
Constant	-0.736	0.367	4.024	0.045	0.479
Test			**χ^2**	***df***	***p*-value**
Omnibus test of model coefficients			18.544	5	0.002*
Hosmer & Lemeshow goodness-of-fit test			7.558	7	0.373

Note * Significant at $p<0.10$
Reference category for gender – female
Reference category for income – >RM30,000

In summary, the results for the regression model for the house money effect implied that male respondents were more likely to be affected by this behavioural bias. It was also evident from the odds ratio for the two highly significant categories of the variable that this tendency could decrease with increasing monthly household income.

The regression model for the endowment effect was presented in Table 4.18. The variable in the equation was a two-way interaction term between monthly household income and age. Holding all other factors constant, the following conclusions were drawn.

- The likelihood of an irrational response was negatively correlated with the age of the respondent.

- Given the same age, all the income categories were less likely than the reference category to choose an irrational response.

Table 4.18

Results of a Multivariate Logistic Regression Model for the Endowment Effect – Retail Investors

Predictor	β	**SE**	**Waldχ^2**	***p*-value**	**Odds Ratio**
Age*Income			15.019	0.005*	
Age*<RM5k	-0.048	0.018	7.558	0.006*	0.953
Age*RM5k-10k	-0.029	0.016	3.456	0.063*	0.971
Age*RM10k-20k	-0.044	0.012	14.092	<0.000*	0.957
Age*RM20k-30k	-0.023	0.013	3.095	0.079*	0.978
Constant	2.022	0.382	28.018	<0.000	7.556
Test			χ^2	***df***	***p*-value**
Omnibus test of model coefficients			17.103	4	0.002*
Hosmer & Lemeshow goodness-of-fit test			2.641	7	0.916

Note * Significant at $p<0.10$
Reference category for income – >RM30,000

In summary, the results from the regression model for the endowment effect implied that the variable age could be a very significant predictor for retail investors. Studies on the effect of this variable on investment decisions showed a decline in cognitive abilities with age (Besedeš, Deck, Sarangi, & Shor, 2011; Korniotis & Kumar, 2011). However, the results from Table 4.16 on the breakeven effect and Table 4.18 on the endowment effect showed that this was true for decisions that involved risky choices but not riskless choices. This finding was consistent with the findings in section 4.6.

4.8. Summary of Findings

On the whole, the results in Table 4.3 were consistent with the findings from existing research on prospect theory. This supported the use of hypothetical decision scenarios with specified responses as an effective measure for decision-making behaviour in behavioural finance research.

Chi-square tests of association revealed no significant difference in the decision-making behaviour between investment professionals and retail investors, which was also consistent with findings from existing research (Chen et al., 2007; Baucells & Rata, 2006; Torngren & Montgomery, 2004). However, the results from the logistic regression analyses in Section 4.7 revealed potential differences in the effect of demographic and socio-economic characteristics on decision-making behaviour within the two types of investors. For example, among retail investors, male respondents exhibited greater loss aversion tendencies; this was reversed among investment professionals. The regression analyses also highlighted the variable monthly household income as common predictor for the behavioural biases under study for both types of investors. Interestingly, among investments professionals, the tendency to succumb to behavioural biases that were linked to risky choices (i.e. the disposition effect and breakeven effect) was higher above a certain threshold income level. The opposite was observed for retail investors for the house money effect.

The finding which was of most interest to the researcher was with regard to the role of experience in decision-making behaviour. There was a distinct pattern in the analysis of the odds ratio in Tables 4.5, 4.6 and 4.7, which suggested that whether or not individuals could learn to overcome their behavioural biases when making financial

decisions could be dependent upon whether the task involved a riskless or risky choice. The results showed that the role of experience (using age, investing experience and type of investor as proxies) in tempering the influence of behavioural biases was more relevant for decisions that involved riskless choices.