

# Behavioural Biases and Investment Decisions during COVID-19: An Empirical Study of Chinese Investors

Ivy S.H. Hii<sup>a</sup>, Xu Li<sup>b</sup> & Haifeng Zhu<sup>c</sup>

**Abstract:** *Due the outbreak of the COVID-19 pandemic, China's economy and securities market were significantly impacted, prompting the need to understand investor behaviour during this emergency. This study investigates the investment behaviour of Chinese investors during the COVID-19 pandemic, focusing on four types of investor biases: representativeness, overconfidence, disposition effect, and herding effect. The study utilized a quantitative research design, collecting data through an online questionnaire and a convenience sampling method from investors who traded in the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Multiple linear regression analysis was employed to examine the impact of behavioural biases on investment decisions during the pandemic. Results showed that representativeness, disposition effect and herding effect significantly influenced investors' investment decisions. This study contributes to the literature on behavioural finance by providing empirical evidence of the impact of behavioural biases on Chinese investors' investment decisions during a crisis. The findings have practical implications for financial institutions to better understand the behaviour of Chinese investors during times of crisis and suggest the need for financial institutions to incorporate behavioural finance principles in their risk management practices.*

**Keywords:** Behavioural biases; Investment decisions; Individual investors; China; COVID-19

**JEL Classification:** G41, G11, D14

---

<sup>a</sup> Corresponding author. Faculty of Business, Curtin University Malaysia, Sarawak, Malaysia; Institute of Capital Market Research, Bukit Damansara, Kuala Lumpur, Malaysia. *Email:* [ivy.hiish@curtin.edu.my](mailto:ivy.hiish@curtin.edu.my). ORCID: 0000-0002-5267-3341

<sup>b</sup> Hong Kong Baptist University, Kowloon Tong, Hong Kong. *Email:* [22410546@life.hkbu.edu.hk](mailto:22410546@life.hkbu.edu.hk)

<sup>c</sup> Beijing Normal University – Hong Kong Baptist University United International College (BNU-HKBU UIC), Xiangzhou, Zhuhai, China. *Email:* [n830021052@alummi.uic.edu.cn](mailto:n830021052@alummi.uic.edu.cn)

## 1. Introduction

The COVID-19 pandemic has disrupted economies and financial markets globally, causing unprecedented uncertainty and volatility. Similarly, in China, the outbreak of COVID-19 in late 2019 resulted in the implementation of stringent measures to control the spread of the virus, including the imposition of a home isolation policy. This policy had significant consequences for Chinese enterprises, with production growth, employment levels, supply speed, and raw material inventory all affected. The Purchasing Managers' Index (PMI) for manufacturing decreased by 14.3% month-on-month, while the non-manufacturing PMI index decreased by 24.5% month-on-month (National Bureau of Statistics of China, 2022). The epidemic's impact on the Chinese economy was also reflected in the financial market, with the CSI 300 index closing down 7.88% on 3 February 2020, with a total of 3,188 stocks down on Shanghai and Shenzhen Stock Exchange, marking the largest drop since 2015 (National Bureau of Statistics of China, 2022).

Despite government efforts to stabilize the market, the stock markets have experienced significant fluctuations since the outbreak of the pandemic. Investors face a multitude of challenges and difficult decisions as they navigate this uncertain terrain, leading to a significant surge in trading volume in the Chinese stock market. Sun and Wu (2021) found that stock returns and trader sentiment reacted negatively following the outbreak of the pandemic, resulting in lower market returns and higher volatility in the Chinese stock market. Additionally, a reversal effect was observed, where market returns and investor sentiment reversed after reaching extremes, even exceeding pre-pandemic levels. This is supported by the performance of the Shanghai Composite Index, which bottomed out at 2646.8 on 19 March 2020 and then rebounded significantly, reaching a high of 3458.8 on 13 July 2020 (Shanghai Stock Exchange, 2022). The high yield of the stock market attracted a substantial number of investors, with the number of investors in the securities market exceeding 200 million as of 25 February 2022, as disclosed by China Securities Depository and Clearing Corporation Limited (Global Times, 2022). Stocks and mutual funds have also attracted significant investor interest, frequently appearing on Chinese social media platforms' popular search lists. Overall, the impact of the COVID-19 pandemic on the Chinese economy and stock market has been significant,

with both experiencing fluctuations and challenges that have affected various sectors and industries, resulting in higher volatility.

As the COVID-19 pandemic has created an unprecedented level of uncertainty in global financial markets, it is therefore crucial to understand how investors make decisions in such a context, particularly in developing countries like China where the impact of behavioural biases and heuristics on investment decisions has been understudied. Previous research in behavioural finance has primarily focused on stock markets in developed countries, and as such, the applicability of these findings to developing countries is limited (Parveen et al., 2021). Moreover, the Chinese securities market is still in its nascent stages and requires improvements in its operating systems. Compared to investors in developed countries, Chinese investors generally receive less investment education and may rely on intuition to trade stocks without adequate financial knowledge (Peng et al., 2022). These factors make Chinese investors more susceptible to behavioural biases and heuristics in their investment decisions (Xu, 2013).

Additionally, despite the significance of the impact of COVID-19 on the Chinese stock market, there has been limited research on the influence of behavioural biases during the pandemic. Several recent studies have explored the turmoil in financial markets brought about by the pandemic and its influence on investors, thereby highlighting the importance of understanding investor behaviour during the pandemic (O'Donnell et al., 2021; Okorie & Lin, 2021). By examining the impact of behavioural biases on investment decisions during a major economic disruption caused by the pandemic, this study also contributes to the existing literature by providing insights into the potential effects of market shocks on investor behaviour and decision-making. This can inform future research and provide valuable guidance for policymakers and investors, not only during the pandemic but also in similar market disruptions caused by other unexpected events in the future.

Therefore, this study aims to fill the research gap by analysing the effect of behavioural biases on investment decisions during the COVID-19 pandemic among Chinese stock investors. Specifically, this study explores the extent to which behavioural biases, such as representativeness, overconfidence, disposition effect and herd mentality, influence investors' decision making and contribute to market volatility during the pandemic. This paper provides recommendations for financial regulators and investors to mitigate the negative impact of behavioural biases on market stability

during crises. It sheds light to the role of behavioural biases in investment decision-making during crises and provide insights into how investors can make more informed investment decisions that promote market stability and reduce financial risk.

## **2. Literature Review**

### **2.1 Theoretical framework**

Traditional financial theory has long been rooted in the assumption that investors are rational and that the market is efficient. According to the efficient market theory, investors form rational expectations about future prices and news or announcements are reflected in stock prices in a reasonable way (Yao et al., 2014). However, market fluctuations and crises have shown that traditional finance theory has failed to fully explain the behaviour of stock prices in the market. The sentiment in the market during times of uncertainty can lead to overreactions or underreactions in investment decisions (Shiller, 2003). Additionally, while trading volume is an important factor in the financial market, the differences in information among investors do not explain the unusually high volume observed in stock markets (Glaser & Weber, 2007).

During times of global crisis, such as the COVID-19 pandemic, it becomes particularly challenging to understand the key characteristics of financial markets, stock returns, and investor behaviour within the traditional framework. Barberis and Thaler's (2003) study supports this notion, suggesting that the traditional framework may not adequately explain investors' behaviour. Consequently, recent research in financial markets has emphasized the need for a new approach to financial theory that recognizes the differences between traditional theory and Behavioural Finance. Behavioural Finance, specifically, has emerged to explain why some investors make decisions that are influenced by their perception of the stock market and their emotional states (Barberis & Thaler, 2003). It is a field that is at the intersection of psychology and finance and investigates the behaviour of investors who deviate from standard assumptions (Yoong & Ferreira, 2013). Furthermore, behavioural finance argues that investment decisions are often asymmetric and irrational due to information asymmetry (Statman et al., 2006). It suggests that investors and markets are not entirely

rational and that some financial phenomena can only be understood within a behavioural finance framework.

In this regard, Bansal (2020) has proposed that the market crash and extreme volatility witnessed during the COVID-19 pandemic should be analysed through the prism of behavioural biases. In response to this call, this study examines the influence of behavioural biases and heuristics on investment decision-making through the lens of behavioural finance. By exploring the potential impact of behavioural finance on investment decisions in the context of the COVID-19 pandemic, this study contributes to the existing literature on financial theory and enhances the understanding of the determinants shaping investment decisions in the context of the pandemic.

## ***2.2 Representativeness and investment decisions***

Representativeness is a cognitive heuristic that can result in erroneous decision-making by leading individuals to consider a particular feature as representative of an entire phenomenon, without evaluating whether that feature is associated with the phenomenon (Tversky & Kahneman, 1982). In the stock market, individuals tend to rely excessively on recent information while making investment decisions. Moreover, they may be more prone to underreact to earnings announcements in the short run and overreact to highly unexpected earnings in the long run, with the latter phenomenon being influenced by representativeness bias (Kaestner, 2006). When investors receive a series of favourable news announcements, they may develop overconfidence and assume that subsequent news will also be positive, resulting in overreaction and overvaluation of the stock (Barberis et al., 1998). Conversely, unfavourable news may lead investors to assume that the trend will continue in a negative direction, causing them to underreact and potentially miss out on opportunities. Psychological biases and heuristics are often utilized by investors to minimize risks associated with decision-making under uncertainty (Prosad et al., 2017). Nevertheless, the representativeness bias can lead to inadequate decision-making, as it precludes the consideration of all potential alternatives before a decision is made. Such biases and heuristics may contribute to market inefficiencies and affect investment decisions.

The COVID-19 pandemic has brought about unprecedented market volatility and uncertainty (Sun & Wu, 2021), which may exacerbate

the representativeness bias in investors. Given the rapid pace at which information is disseminated about COVID-19 and its impact on the financial markets, the tendency to rely on recent trends and information is likely to be amplified during times of crisis, as investors might seek to quickly adapt to changing market conditions. In particular, investors may rely too heavily on the most recent and salient information related to the pandemic, such as news of vaccine efficacy or infection rates, and use it as a representative feature of the overall market trend. This can lead to overreactions and underreactions to market events and potentially exacerbate market volatility. Moreover, representativeness bias occurs when individuals rely on past events to predict future outcomes. For instance, if a company shows consistent profits, investors may assume that it will continue to grow, leading them to view the company as a favourable investment opportunity (Kartini & Nahda, 2021). The pandemic-induced economic disruption may create new salient features that investors may use as a representative feature to make decisions. For instance, investors may overvalue stocks in the healthcare or online shopping sectors, which have seen increased demand during the pandemic, while undervaluing stocks in other sectors that have been negatively impacted by the pandemic.

Therefore, we hypothesize that:

*H1: In the context of COVID-19, representativeness negatively affects the investment decisions of investors in the Chinese stock market.*

### **2.3 Overconfidence and investment decisions**

According to Barber and Odean (2001), psychologists have identified that overconfidence can result in individuals overvaluing their knowledge, undervaluing risk, and inflating their perceived capability to control events. Studies have shown that investing in the stock market is an activity in which individuals tend to display a significant degree of overconfidence (Baker & Nofsinger, 2002). Despite the fact that the stock market is inherently unpredictable, even experts are more prone to overconfidence than novices (Griffin & Tversky, 1992). It is believed that individuals who possess a heightened sense of confidence in their investment capabilities may be more inclined to work as traders or actively manage their own investment

portfolios, leading to a selection bias favouring overconfidence within the investor group.

Research has shown that overconfidence is associated with investment decision (Grežo, 2021). Besides, overconfidence is often more pronounced during times of crisis or uncertainty, such as during economic downturns or major world events (Rachlin, 2004). This may be due to a variety of factors, including a heightened need for control and the desire to feel more certain in uncertain situations. In the context of the COVID-19 pandemic, the unprecedented level of uncertainty and volatility in the stock market may have exacerbated overconfidence among investors. The fear of missing out on potential gains, coupled with the desire to take control in a situation that feels unpredictable, may have led some investors to overvalue their knowledge and skills, underestimate risk, and make overly confident investment decisions. Besides, studies have also associated overconfidence with optimism (Hilton et al., 2011). Investors who hold an optimistic outlook may view the stock market crash caused by the COVID-19 pandemic as a chance to earn more profit and may consequently increase their participation in stock trading (Talwar et al., 2021; Baker et al., 2020).

Therefore, we hypothesize that:

*H2: In the context of COVID-19, overconfidence negatively affects the investment decisions of investors in the Chinese stock market.*

#### **2.4 Herding effect and investment decisions**

The phenomenon of herding effect in financial markets is a well-known occurrence whereby investors' financial decisions are significantly influenced by others, leading them to follow the investment decisions of other traders (Devenow & Welch, 1996). It is characterized by a greater reliance on collective information relative to other sources of information. Herding behaviour can result in deviations from the stock price to its intrinsic value and may cause investors to miss out on potentially profitable investment opportunities (Tan et al., 2008). Based on the herding theory, investors tend to make the same investment decisions to buy or sell shares in the stock market as the public decides to do, which can result in market inefficiency. The herding effect brings investors together to form small groups, using this mentality to counteract the unfamiliar surroundings and gain information

support and a sense of security (Caparrelli et al., 2004).

During the COVID-19 pandemic, the herding effect can become more pronounced in financial markets. Talwar et al. (2021) indicated that higher herding bias during COVID-19 increases the trading activity among millennials and their recommendation intentions. Research has also shown that investors may be more likely to follow the investment decisions of others when faced with uncertainty and heightened volatility (Aharon, 2021). For example, during the early stages of the COVID-19 pandemic, there was a significant sell-off in global stock markets. This led to a situation where investors were more likely to follow the lead of others in selling off their investments, rather than taking a more rational and informed approach to investment decision-making. Similarly, investors may follow the crowd in a panic-driven rush to buy certain stocks.

Therefore, we hypothesize that:

*H3: In the context of COVID-19, herding effect negatively affects the investment decisions of investors in the Chinese stock market.*

## **2.5 Disposition effect and investment decisions**

The disposition effect is a phenomenon in which investors tend to sell assets that have made gains to realize profits, while holding onto loss-making assets in the hope that they will eventually recover their value (Frazzini, 2006). This behaviour is related to the concept of loss aversion, as proposed by Tversky and Kahneman (1992), which suggests that individuals are more averse to losses than they are inclined to seek out gains. In other words, people become more risk-averse after experiencing gains and more risk-seeking after experiencing losses. As a result, investors may be more likely to hold onto declining assets rather than sell them, as the latter option is perceived as riskier (Shefrin & Statman, 1985).

As stock prices plummeted in response to the COVID-19 pandemic, investors were faced with significant losses in their portfolios. The disposition effect can exacerbate such situation, as investors may be more inclined to hold onto their losing investments in the hope of future gains, rather than cutting their losses and selling off their holdings. This can lead to a reluctance to sell off stocks at a loss, leading to a portfolio that is overly concentrated in underperforming assets, which can increase the



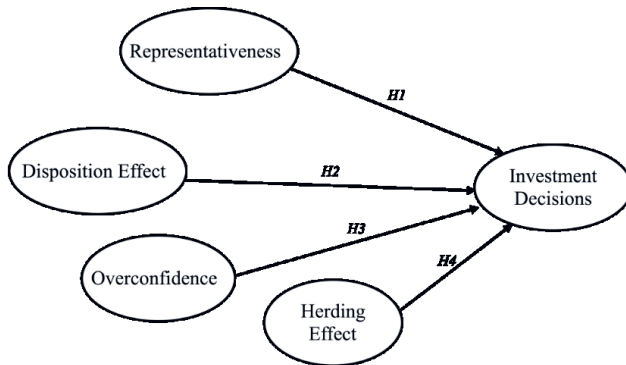
risk of further losses (Kartini & Nahda, 2021). Moreover, the disposition effect can also lead to missed investment opportunities during times of crisis. As stock prices fall, investors may be more hesitant to purchase stocks that have previously experienced significant losses. This can lead to missed opportunities for gains as the market rebounds, as investors may be hesitant to purchase stocks that have experienced losses, even if they are fundamentally sound.

Therefore, we hypothesize that:

*H4: In the context of COVID-19, disposition effect negatively affects the investment decisions of investors in the Chinese stock market.*

Based on the hypotheses presented above, a conceptual model is proposed as illustrated in Figure 1.

**Figure 1:** Conceptual Model



Source: Authors' own.

### 3. Methodology

#### 3.1 Sample and procedures

The data collection for this study involved the utilization of online survey questionnaires, which was necessitated by the constraints imposed by the COVID-19 pandemic on in-person activities. The target population comprised individual and institutional investors who traded on the Shanghai

and Shenzhen Stock Exchange during the COVID-19 period. Convenience sampling method was employed in distributing online questionnaires to the identified population. To ensure that the respondents are part of the target population for the study, a screening question asking if they have traded on the Shanghai or Shenzhen Stock Exchange during the COVID-19 pandemic period was included. The sample size requirements were determined based on the G\*Power analysis, which indicates that a minimum of 85 useable responses are required to achieve a power of 80% at an effect size of 0.15. The questionnaires were distributed through the questionnaire platform on WeChat between 15 January to 20 February 2022, resulting in 321 responses. After data cleaning, a total of 308 questionnaires were considered valid and complete for the final analysis. The collected data were analysed using Statistical Package for the Social Sciences (SPSS) software.

### 3.2 Measures

The questionnaire consisted of two sections. The first section sought to gather basic demographic information, including gender, age, total trading experience, investment amount, employment status, and stock holding duration of the respondents. The second part of the questionnaire was designed to assess the investors' level of behavioural bias and investment decision-making. This section covered behavioural heuristics, overconfidence, disposition effect, herding effect, and investment decision. The questionnaire utilized a five-point Likert scale, with 1 = disagree to 5 = agree. In order to obtain a composite measure of each construct, the responses for each item were summed. The resulting total score for each variable provided an indication of the magnitude of behavioural biases present in the participants' investment decision-making. Higher scores on the composite measures indicate a greater degree of the specific bias being assessed.

Representativeness was measured using items adapted from Rasheed et al. (2016). Sample items included in the questionnaire were “*I tend to invest in well-known stocks rather than those that are unfamiliar, I avoid investing in poorly performing companies and use trend analysis in my investment decisions*”. The questionnaire items for overconfidence were adopted from Wood and Zaichkowsky (2004) and included items such as respondents' perceived knowledge of the Chinese stock market, belief

in their personal skills and knowledge being sufficient to outperform the market and attributing past profitable experiences to their own skills and understanding. Respondents were also asked about their tendency to buy stocks recommended by friends or co-workers. As for disposition effect, the items were adopted from Waweru et al. (2008) and included items, such as respondents' tendency to sell as soon as the stock price starts to rise and their tendency to continue holding a stock if its current market price is greater than the purchase price, even if the stock has performed poorly in the past. Herding effect was assessed using items adopted from Kengatharan (2014) and included items related to the extent to which respondents' investment decisions were influenced by the decisions of other investors, such as the types of stocks chosen, the volume of stocks bought or sold, and the reactions to changes in the stock market. Respondents were asked about their tendency to quickly react to changes in other investors' decisions and mimic their reactions to the stock market.

Last, this study adopted sample items related to investment decisions from Khan et al. (2017), which included respondents' preferences for investing in certain stocks, decisions based on historical information, investments in heavily traded stocks, preferences for stocks of companies with high exposure, investments in stocks that had outperformed the market, and investments in stocks that had recently lost money with the expectation that they would recover in the future. The responses were rated on a five-point Likert scale, with higher scores indicating a greater tendency towards making optimal investment decisions.

## **4. Results**

### ***4.1 Respondent profile***

As shown in Table 1, the respondent profile of this study indicated that there were slightly more male participants than female participants. The majority of respondents fell within the age range of 21-39 years old, with the largest group being 21-29 years old, followed by the 30-39 years old group. This could be attributed to the use of online questionnaires, which may have attracted younger participants who frequently browse apps online. In terms of employment and education, most respondents were students or employees, and the majority of them were undergraduate students. The highest group

of trading experience was between 1 and 2 years, with the most common amount of investment being less than 50,000 yuan. Notably, a significant portion of respondents invested less than 10,000 yuan. The highest group of stock holding time was more than six months, while the smallest group held stocks for just one day.

**Table 1:** Respondent Profile

Category	Frequency	Percent
<b>Gender</b>		
Male	168	54.5
Female	140	45.5
<b>Age</b>		
Under 20	15	4.9
21 – 29	169	54.9
30 – 39	76	24.7
40 – 49	35	11.4
Above 50	13	4.2
<b>Total Trading Experience</b>		
Less than 1 year	72	23.4
1 - 2 years	117	38
3 - 4 years	77	25
4 - 5 years	14	4.5
More than 5 years	28	9.1
<b>Amount of Investment</b>		
Less than 10000	115	37.3
10000 - 49999	114	37
50000 - 100000	48	15.6
More than 100000	31	10.1
<b>Employment Status</b>		
Student	132	42.9
Employee	160	51.9
Unemployed	5	1.6
Self-Employed	11	3.6
<b>Stock Holding Time</b>		
One day (T + 1 Trading)	17	5.5
More than one day but not over one work	25	8.1
More than one week but not over one month	68	22.1
More than one month but not over three months	54	17.5
More than three months but not over six months	52	16.9
more than six months	92	29.9

Category	Frequency	Percent
<b>Highest Education Level</b>		
High school or lower	21	6.8
Undergraduate	244	79.2
Masters	35	11.4
PhD	4	1.3
Others	4	1.3

#### 4.2 Reliability

Prior to data analysis and modelling, the reliability of the questionnaire data was assessed using SPSS. According to Sekaran and Bougie (2013), reliability refers to the extent to which a measurement is free from random or unstable error. The Cronbach's alpha coefficient was utilized to verify the reliability of the measurement model. A measurement model is considered acceptable when the Cronbach's alpha coefficient is above 0.6 (Sekaran & Bougie, 2013). The output of Cronbach's alpha coefficient for each variable is presented in Table 2. All variables demonstrated a Cronbach's alpha coefficient greater than 0.6, indicating acceptable internal consistency of the measurement model. Therefore, it can be concluded that representativeness, disposition effect, herding effect, overconfidence, and investment decisions exhibit satisfactory internal consistency.

**Table 2:** Descriptive and Reliability Statistics

Variables	Mean	Variance	Std. Deviation	Items	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items
Representativeness	23.13	10.674	3.267	6	0.677	0.688
Overconfidence	9.160	5.680	2.383	3	0.724	0.724
Disposition Effect	8.860	5.695	2.386	3	0.642	0.636
Herding Effect	14.05	8.571	2.928	4	0.790	0.791
Investment Decisions	24.85	12.961	3.600	7	0.650	0.651

### 4.3 Correlation analysis

The Pearson correlation coefficients, as presented in Table 3, were utilized to assess the degree of correlation between the variables. The results indicated that there was no evidence of collinearity among the variables of representativeness, overconfidence, disposition effect, and herding effect, as indicated by the absolute values of the Pearson correlation coefficients being less than 0.473 (Pallant, 2011).

**Table 3:** Pearson Correlation Analysis Between Variables

Variable	1	2	3	4	5
1. Investment Decisions	-	-0.392**	-0.322**	-0.316**	-0.473**
2. Representativeness		-	0.284**	0.132*	0.409**
3. Overconfidence			-	0.289**	0.304**
4. Disposition Effect				-	0.294**
5. Herding Effect					-

Note: \* $p < 0.05$ . \*\* $p < 0.01$ .

### 4.4 Multicollinearity test

Multicollinearity refers to the occurrence of high correlations between two or more independent variables in a regression model. A tolerance value of less than 0.1 is generally regarded as an indicator of severe multicollinearity (Pallant, 2011). Meanwhile, the Variance Inflation Factor (VIF) also provides a measure of the degree of multicollinearity between the independent variables. A high VIF value indicates strong covariance between independent variables. A VIF value greater than or equal to 10 is generally considered an indication of serious multicollinearity between the independent variables (Pallant, 2011). The results in Table 4 indicate that the tolerance values for the four independent variables (representativeness, overconfidence, herding effect, and disposition effect) were all greater than 0.1. Moreover, the VIF values of the four independent variables were all less than 10. Therefore, it can be concluded that there was no issue of multicollinearity between the four independent variables in the regression model.

**Table 4:** Variance Inflation Factor (VIF) and Tolerance Values

	B	Std. Error	$\beta$	t	p	Tol	VIF
(Constant)	31.641	1.346		23.508	0.000		
Representativeness	-.234**	0.058	-0.212	-4.010	0.000	0.804	1.243
Overconfidence	-.186*	0.079	-0.123	-2.364	0.019	0.835	1.198
Disposition Effect	-.247**	0.077	-0.164	-3.218	0.001	0.869	1.151
Herding Effect	-.369**	0.067	-0.300	-5.493	0.000	0.756	1.324

Note: \* $p < 0.05$ . \*\* $p < 0.01$ .

#### 4.5 Multiple linear regression

Hierarchical multiple regression analysis was conducted to assess the influence of behavioural biases on investment decisions. Table 5 presents the results of hierarchical multiple linear regression. In Model 1, demographic information, such as gender, age, amount of investment, experience, employment status, stock holding time, and education, were included. All of the demographic variables were found to be statistically insignificant, except for total trading experience and education level. Model 2 was constructed by adding four independent variables to Model 1, containing the seven demographic information variables and the four independent variables. The effect of representativeness ( $\beta = -0.221$ ,  $p < 0.01$ ), disposition effect ( $\beta = -0.193$ ,  $p < 0.01$ ), and herding effect ( $\beta = -0.298$ ,  $p < 0.01$ ) on investment decision were statistically significant, while overconfidence ( $\beta = -0.061$ ,  $p = 0.286$ ) was found to be insignificant. Therefore, H1, H3, and H4 were supported, while H2 was not supported. The results showed that only the total trading experience was significant among the control variables.

**Table 5:** Hierarchical Multiple Regression Analysis

	B	Std. Error	$\beta$	T	R <sup>2</sup>
<b>Model 1</b>					
Gender	-0.253	0.422	-0.035	-0.598	0.076
Age	0.063	0.314	0.016	0.202	
Total Trading Experience	-1.066**	0.245	-0.343	-4.356	
Amount of Investment	0.248	0.27	0.067	0.919	
Employment Status	0.258	0.394	0.049	0.654	
Stock Holding Time	0.137	0.145	0.058	0.944	
Education	-0.054**	0.346	-0.009	-0.156	

	B	Std. Error	$\beta$	T	R <sup>2</sup>
<b>Model 2</b>					
Gender	0.194	0.359	0.027	0.539	0.359
Age	0.042	0.27	0.011	0.155	
Total Trading Experience	-0.674**	0.211	-0.217	-3.191	
Amount of Investment	0.148	0.234	0.04	0.632	
Employment Status	0.111	0.335	0.021	0.331	
Stock Holding Time	-0.136	0.124	-0.058	-1.096	
Education	-0.025	0.292	-0.004	-0.085	
Representativeness	-0.243**	0.058	-0.221	-4.168	
Overconfidence	-0.092	0.086	-0.061	-1.069	
Disposition Effect	-0.291**	0.077	-0.193	-3.78	
Herding Effect	-0.367**	0.068	-0.298	-5.418	

Note: \* $p < 0.05$ . \*\* $p < 0.01$ .

The R-square findings in this study indicated the extent to which the demographic information variables and independent variables accounted for the variance in investment decisions. In Model 1, the R-square was 0.076, which indicated that only 7.6% of the variation in investment decisions could be explained by the demographic information variables. This suggested a low explanatory power of the model. However, in Model 2, the R-square increased to 0.359, indicating that 35.9% of the variation in investment decisions could be explained by both the demographic information variables and the independent variables. This represented a relatively high explanatory power of the model. The findings suggested that while demographic information alone was not sufficient to explain investment decisions, the inclusion of independent variables such as representativeness, disposition effect, herding effect, and overconfidence improved the model's explanatory power.

## 5. Discussion

The present study aims to investigate the influence of behavioural biases on investment decisions among individual Chinese investors during the COVID-19 pandemic. The results showed that representativeness, disposition effect, and herding effect were significantly and negatively associated with investment decisions. It suggested that the more severe the behavioural



biases, the worse the investment decisions made by individual Chinese investors. The COVID-19 pandemic has caused unprecedented market volatility and heightened uncertainty, which has made it challenging for investors to make sound investment decisions. Consequently, investors may have resorted to relying on representativeness, disposition effect, and herding effect more heavily than usual, which could have led to suboptimal investment decisions. Specifically, the representativeness bias may have caused investors to overemphasize recent market trends and extrapolate them to the future, leading to investment decisions that did not fully consider underlying fundamentals. The disposition effect may have led investors to hold onto losing positions longer than necessary, in an effort to avoid the pain of realizing a loss. The herding effect may have caused investors to follow the crowd and make investment decisions based on others' actions, rather than independent analysis. Collectively, these biases may have contributed to the negative effects on investment decisions as revealed in this study. This finding is consistent with previous research that has shown that the presence of behavioural biases can lead to suboptimal investment decisions (Parveen et al., 2021).

On the other hand, overconfidence was not significantly related to investment decisions. This finding is inconsistent with the findings from previous research (Grežo, 2021; Rachlin, 2004). One possible explanation for this finding in the context of COVID-19 is that the pandemic may have heightened investors' awareness of stock market risks. China has a strict approval system for opening securities accounts, and before opening a securities account, all investors are strictly informed of securities risks and test risk tolerance. This may have strengthened investors' awareness of stock market risks to a certain extent, making them more cautious and less likely to be overconfident. As highlighted by Parveen et al. (2021), the prediction on the economy and industry changed overconfident investors' behaviour by 41.8% during the pandemic.

## **6. Conclusion and Implication**

In conclusion, this study investigated the impact of four types of behavioural biases on the investment decisions of Chinese investors during the COVID-19 pandemic. The findings suggest that representativeness bias, disposition effect, and herding effect significantly influenced investment

decisions, while the impact of overconfidence bias was not found to be significant.

This study adds to the theoretical understanding of behavioural finance by shedding light on the influence of behavioural biases on Chinese investors' investment decisions during a crisis, specifically the COVID-19 pandemic. This research expands the current literature by providing evidence of the applicability of behavioural finance theories in a developing country context, where the influence of heuristics and biases on investment decisions has been underexplored. The findings suggest that Chinese investors are subject to behavioural biases and heuristics, which affect their investment decisions. Additionally, this study contributes to the existing literature on investor behaviour by examining the influence of crisis or market shocks on individuals' investment decisions. By exploring the impact of behavioural biases on investors' decision-making during a major economic disruption caused by the pandemic, this research provides valuable insights into the potential effects of unexpected events on investor behaviour and decision-making.

The findings of this study bear important practical implications for various stakeholders, including individual investors, financial professionals, policymakers, and regulators in China. The observed adverse impact of behavioural biases on investment decisions highlights the significance of mitigating such biases through appropriate interventions. Hence, individual investors must become cognizant of these biases and undertake necessary measures to counteract their influence on investment decision-making. Furthermore, financial professionals are encouraged to acknowledge the impact of these biases and collaborate with investors to promote rational investment behaviour. On the regulatory front, policymakers and regulators also play a crucial role in regulating the securities market and should consider the implications of behavioural biases in their decision-making processes, thus developing appropriate policies and regulations that mitigate such biases.

## **7. Limitation and Future Directions**

Despite the contributions of this study, several limitations need to be acknowledged. Firstly, there is a potential for response bias when using survey data. Respondents may provide inaccurate or incomplete information

due to social desirability bias, where they provide answers that they believe are more socially acceptable or desirable. Additionally, respondents may have difficulty recalling certain information or may misinterpret the survey questions. As such, the accuracy of self-reported investment behaviour may be affected as investors may not always accurately report their own biases or behaviours. Future research could consider using objective measures, such as analysing actual trading behaviour as a more accurate representation of investor behaviour. Secondly, this study's sample was predominantly made up of young individual investors, which limits the generalizability of the results to other age groups and institutional investors. Future research should strive to gather a more diverse sample to increase the generalizability of the results. Moreover, this study did not cover all the behavioural biases that could influence investment decisions, suggesting the need for further research to identify additional factors that could impact investment decisions. Future research should also consider conducting comparative studies across different securities markets to identify similarities and differences in the influence of behavioural biases on investment decisions. Finally, future research could explore the effectiveness of various interventions to mitigate the impact of behavioural biases on investment decisions, thus providing valuable insights to financial professionals and policymakers in promoting rational investment behaviour.

## References

- Aharon, D. Y. (2021). Uncertainty, fear and herding behaviour: Evidence from size-ranked portfolios. *Journal of Behavioural Finance*, 22(3), 320-337. <https://doi.org/10.1080/15427560.2020.1774887>
- Baker, H. K., & Nofsinger, J. R. (2002). Psychological biases of investors. *Financial Services Review*, 11(2), 97.
- Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, 10(4), 742-758. <https://doi.org/10.3386/w26945>
- Bansal, T. (2020). Behavioural finance and COVID-19: Cognitive errors that determine the financial future. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3595749>

- Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1), 261-292. <https://doi.org/10.1162/003355301556400>
- Barberis, N., & Thaler, R. H. (2003). Chapter 18 - A survey of behavioural finance. In *Handbook of the Economics of Finance* (Vol. 1, pp. 1053–1128). Elsevier.
- Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307-343. <http://dx.doi.org/10.3386/w5926>
- Caparrelli, F. D., Arcangelis, A. M., & Cassuto, A. (2004). Herding in the Italian stock market: a case of behavioural finance. *Journal of Behavioural Finance*, 5(4), 222–230. [https://doi.org/10.1207/s15427579jpfm0504\\_5](https://doi.org/10.1207/s15427579jpfm0504_5)
- Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40(3-5), 603-615. [https://doi.org/10.1016/0014-2921\(95\)00073-9](https://doi.org/10.1016/0014-2921(95)00073-9)
- Frazzini, A. (2006). The disposition effect and underreaction to news. *The Journal of Finance*, 61(4), 2017-2046. <https://doi.org/10.1111/j.1540-6261.2006.00896.x>
- Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review*, 32, 1-36. <https://doi.org/10.2139/ssrn.471925>
- Grežo, M. (2021). Overconfidence and financial decision-making: a meta-analysis. *Review of Behavioural Finance*, 13(3), 276-296. <https://doi.org/10.1108/rbf-01-2020-0020>
- Griffin, D., & Tversky, A. (1992). The weighing of evidence and the determinants of confidence. *Cognitive Psychology*, 24(3), 411-435. <https://doi.org/10.1017/cbo9780511808098.015>
- Hilton, D., Regner, I., Cabantous, L., Charalambides, L., & Vautier, S. (2011). Do positive illusions predict overconfidence in judgment? A test using interval production and probability evaluation measures of miscalibration. *Journal of Behavioural Decision Making*, 24(2), 117–139. <https://doi.org/10.1002/bdm.678>
- Kaestner, M. (2006). Investors' misreaction to unexpected earnings: Evidence of simultaneous overreaction and underreaction. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.868346>

- Kartini, K., & Nahda, K. (2021). Behavioural biases on investment decision: A case study in Indonesia. *The Journal of Asian Finance, Economics and Business*, 8(3), 1231-1240. <https://doi.org/10.13106/jafeb.2021.vol8.no3.1231>
- Kengatharan, L., & Kengatharan, N. (2014). The influence of behavioural factors in making investment decisions and performance: Study on investors of Colombo Stock Exchange, Sri Lanka. *Asian Journal of Finance & Accounting*, 6(1), 2, 1-23. <http://dx.doi.org/10.5296/ajfa.v6i1.4893>
- Khan, H. H., Naz, I., Qureshi, F., & Ghafoor, A. (2017). Heuristics and stock buying decision: Evidence from Malaysian and Pakistani stock markets. *Borsa Istanbul Review*, 17(2), 97–110. <https://doi.org/10.1016/j.bir.2016.12.002>
- National Bureau of Statistics of China. (2022, March 1). *Purchasing Managers' Index* (PMI). <https://data.stats.gov.cn/easyquery.htm?cn=A01>
- O'Donnell, N., Shannon, D., & Sheehan, B. (2021). Immune or at-risk? Stock markets and the significance of the COVID-19 pandemic. *Journal of Behavioural and Experimental Finance*, 30, 100477. <https://doi.org/10.1016/j.jbef.2021.100477>
- Okorie, D. I., & Lin, B. (2021). Adaptive market hypothesis: The story of the stock markets and COVID-19 pandemic. *The North American Journal of Economics and Finance*, 57, 101397, 1-10. <https://doi.org/10.1016/j.najef.2021.101397>
- Pallant, J. (2011). *SPSS Survival Manual: A Step by Step Guide to Data Analysis Using SPSS, 4th edition*. McGraw Hill.
- Parveen, S., Satti, Z. W., Subhan, Q. A., Riaz, N., Baber, S. F., & Bashir, T. (2021). Examining investors' sentiments, behavioural biases and investment decisions during COVID-19 in the emerging stock market: A case of Pakistan stock market. *Journal of Economic and Administrative Sciences*. <https://doi.org/10.1108/JEAS-08-2020-0153> (ahead-of-print)
- Peng, C., She, P. W., & Lin, M. K. (2022). Financial literacy and portfolio diversity in China. *Journal of Family and Economic Issues*, 43(3), 452-465. <https://doi.org/10.1007/s10834-021-09810-3>
- Prosad, J. M., Kapoor, S., Sengupta, J., & Roychoudhary, S. (2017). Overconfidence and disposition effect in Indian equity market: An empirical evidence. *Global Business Review*, 19(5), 1303-1321. <https://doi.org/10.1177/0972150917726660>

- Rachlin, H. (2004). *The Science of Self-Control*. Harvard University Press.
- Rasheed, A., Wen, W., Gao, F., Zhai, S., Jin, H., Liu, J., Guo, Q., Zhang, Y., Dreisigacker, S., Xia, X., & He, Z. (2016). Development and validation of KASP assays for genes underpinning key economic traits in bread wheat. *Theoretical and Applied Genetics*, 129(10), 1843–1860. <https://doi.org/10.1007/s00122-016-2743-x>
- Sekaran, U., & Bougie, R. (2013). *Research Methods for Business: A Skill-Building Approach*. John Wiley & Sons, Inc.
- Shanghai Stock Exchange. (2022, March 25). *Price trends*. <http://www.sse.com.cn/market/price/trends/>
- Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3), 777-790. <https://doi.org/10.1111/j.1540-6261.1985.tb05002.x>
- Shiller, R. J. (2003). From Efficient Markets Theory to Behavioural Finance. *The Journal of Economic Perspectives*, 17(1), 83–104. <https://doi.org/10.1257/089533003321164967>
- Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. *The Review of Financial Studies*, 19(4), 1531-1565. <https://doi.org/10.2139/ssrn.168472>
- Sun, Y., Wu, M., Zeng, X., & Peng, Z. (2021). The impact of COVID-19 on the Chinese stock market: sentimental or substantial? *Finance Research Letters*, 38, 101838. <https://doi.org/10.1016/j.frl.2020.101838>
- Talwar, M., Talwar, S., Kaur, P., Tripathy, N., & Dhir, A. (2021). Has financial attitude impacted the trading activity of retail investors during the COVID-19 pandemic? *Journal of Retailing and Consumer Services*, 58, 102341. <https://doi.org/10.1016/j.jretconser.2020.102341>
- Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behaviour in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal*, 16(1–2), 61–77. <https://doi.org/10.1016/j.pacfin.2007.04.004>
- Total stock accounts exceed 200m, indicating attractiveness of Chinese equities. (2022, February 26). *Global Times*. Retrieved March 15, 2022, from <https://www.globaltimes.cn/page/202202/1253252.shtml>.
- Tversky, A., & Kahneman, D. (1982). Judgment under uncertainty: Heuristics and biases. In *Judgment under Uncertainty* (pp. 3–20). Cambridge University Press.
- Tversky, A., & Kahneman, D. (1992). Advances in prospect

- theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4), 297-323. <https://doi.org/10.1017/cbo9780511803475.004>
- Waweru, N. M., Munyoki, E., & Uliana, E. (2008). The effects of behavioural factors in investment decision-making: A survey of institutional investors operating at the Nairobi Stock Exchange. *International Journal of Business and Emerging Markets*, 1(1), 24. <https://doi.org/10.1504/ijbem.2008.019243>
- Wood, R., & Zaichkowsky, J. L. (2004). Attitudes and trading behaviour of stock market investors: A segmentation approach. *The Journal of Behavioural Finance*, 5(3), 170-179. [https://doi.org/10.1207/s15427579jpfm0503\\_5](https://doi.org/10.1207/s15427579jpfm0503_5)
- Xu, X. (2013). The Research on cognitive bias, emotional bias and behavioural bias in financial markets. *China Northeast Normal University*. Retrieved from <https://kns.cnki.net/KCMS/detail/detail.asp?xdbname=CMFD201401&filename=1013363988.nh>
- Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics & Finance*, 29, 12–29. <https://doi.org/10.1016/j.iref.2013.03.002>
- Yoong, J. & Ferreira, V.R.D.M. (2013). Improving financial education effectiveness through behavioural economics: OECD key findings and way forward, *OECD Publishing*, 1926-1982. [https://www.oecd.org/daf/fin/financial-education/TrustFund2013\\_OECDImproving\\_Fin\\_Ed\\_effectiveness\\_through\\_Behavioural\\_Economics.pdf](https://www.oecd.org/daf/fin/financial-education/TrustFund2013_OECDImproving_Fin_Ed_effectiveness_through_Behavioural_Economics.pdf)