



Vaasan yliopisto
UNIVERSITY OF VAASA

Mira Jokisalo

Study of Behavioral Biases – evidence from China and US

School of Accounting and Finance
Bachelor's thesis
Finance

Vaasa 2025

UNIVERSITY OF VAASA**School of Accounting and Finance**

Author: Mira Jokisalo
Title of the Thesis: Study of Behavioral Biases – evidence from China and US
Degree: Bachelor of Science in Economics and Business Administration
Programme: Finance
Supervisor: Veda Fatmy
Year: 2025 **Sivumäärä:** 38

ABSTRACT:

The purpose of this thesis is to examine overconfidence, loss aversion and herding, and how these biases appear and influence on market in China and US. The literature review confirms these behavioral biases presence in both markets with distinct manifestations. Chinese investors trade frequently due to overconfidence, while US investors react asymmetrically to market shocks. Loss aversion leads to a reluctance to sell in China, while US professionals take more risks to recover losses. Chinese herding behavior leads to price bubbles, while US investors follow macroeconomic trends. The results highlight the need for further research using consistent methodologies.

KEYWORDS: Behavioral bias, Behavioral finance, Overconfidence, Loss aversion, Herding

Contents

1	Introduction	5
1.1	Purpose of the thesis	6
1.2	Structure of the thesis	7
2	Theoretical Background	9
2.1	Efficient Market Hypothesis (EMH)	9
2.2	Capital Asset Pricing Model (CAPM)	10
2.3	Behavioral Finance	12
2.3.1	Overconfidence	13
2.3.2	Loss aversion	15
2.3.3	Herding	17
3	Behavioral biases in China and US	20
3.1	Evidence from China	20
3.2	Evidence from the US	26
4	Conclusion	32
	References	34

Figures

Figure 1. Relationship between herding behavior index, price bubble index and stock market prices. (Wang & Zhao, 2024)

1 Introduction

Financial markets are subject to human behavior, and market participants do not always act rationally. Investors' decisions can often be based on emotions, past experiences or other cognitive biases such as overconfidence, loss aversion and herding. Existing literature offers a broad perspective on various behavioral biases, leading to diverse findings on their nature and effects. For instance, Daniel et al. (1998) find that overconfidence occurs in tasks requiring judgment, while Odean (1998) argues that investors may overestimate the accuracy of their own information, which can lead to an underestimation of other available information.

These biases influence investors' behavior in a way that is at odds with traditional financial theories that assume investors act rationally. This assumption is the cornerstone of the Efficient Market Hypothesis (EMH), and many asset pricing models such as the Capital Asset Pricing Model (CAPM). The fundamental idea behind these theories is that asset prices fully reflect all available information and that investors make logical, utility-maximizing decisions.

Behavioral finance has received increasing attention in recent decades, challenging traditional assumptions about market efficiency. Behavioral finance takes into account psychological factors and seeks to understand how and why psychological biases affect decision-making and market dynamics. By incorporating psychological insights into financial analysis, behavioral finance provides explanations for phenomena such as speculative bubbles, excess volatility, and investor sentiment, offering a deeper insight into market behavior.

However, other factors such as cultural, economic and political elements, can also influence investors' behavior and decision-making and potentially trigger behavioral biases. For example, Feng (2001) finds in his research that political instability and uncertainty have a negative impact on investment. Each market has unique characteristics shaped by these factors, influencing investors behavior. Consequently, when examining different

market areas, various behavioral biases may manifest to different extents, or not at all. Moreover, multiple biases can occur simultaneously or reinforce each other.

By reviewing existing literature, this study examines three behavioral biases separately: overconfidence, loss aversion and herding. Additionally, it explores how these biases manifest in two major markets, China and the US. The motivation for selecting these markets is not only because they are the largest financial markets globally but also because of their distinct characteristics.

For example, Yu et al. (2020) study the transfer of information from different sectors and find that in the Chinese stock market, the banking sector is the main information source, while in the US it is energy sector. Similarly, Zhang et al. (2019) note that China's economic policy uncertainty increases before the 2008 financial crisis but declines afterward, whereas US economic policy uncertainty dominated and spread to global stock markets. These examples highlight structural differences between the two markets, which justify a comparative approach to study how behavioral biases challenge traditional financial theories across different economic environments.

The practical implications of this research are valuable for investors and market participants in general. Understanding the psychological biases that influence decision-making can lead to more informed and rational investment choices, which can improve investment performance. By delving into the evidence of behavioral biases in the markets of China and the United States, the study enhances the understanding of regional similarities or differences in market reactions, which can be valuable for international operators.

1.1 Purpose of the thesis

The main purpose of this thesis is to investigate whether overconfidence, loss aversion and herding exist in China and the United States. By reviewing the existing literature, this

study highlights the key behavioral biases in these markets and examines their potential differences and implications. Each selected behavioral bias is treated separately.

Behavioral biases are part of human cognitive structures, meaning that their occurrence is not solely dependent on external factors. Previous literature shows that behavioral biases are present across different individuals. Liu et al. (2016) show in their study that both institutional and retail investors are overconfident, especially in up markets. Dennie & Vanderbroucke (2004) find that loss aversion is strongly correlated with education level, indicating that more educated individuals exhibit a greater tendency toward loss aversion. Li & Wang (2017) point out that institutional investors and retail investors follow each other. Since previous studies show that behavioral biases are observed across different groups of investors, it is reasonable to assume that they also persist across different markets. Based on this, the first hypothesis is:

H1: All three behavioral biases exist in both the Chinese and US markets.

If there is evidence of behavioral biases in the Chinese or US markets, this study will further explore how these biases manifest and how they affect differently. Previous studies indicate that market areas have their own specific characteristics that have an impact on different behavioral biases. For example, Garcia et al. (2014) highlight that Western cultures such as the United States place more emphasis on individuality, while Asian cultures, including China, emphasise community. Hence, the second hypothesis is:

H2: All three behavioral biases manifest and occur differently in China and the US.

1.2 Structure of the thesis

The structure of the thesis is as follows. A chapter on theoretical background follows the introduction. It discusses the Efficient Market Hypothesis (EMH), the Capital Asset Pricing Model (CAPM), Behavioral Finance and describes the selected behavioral biases of

overconfidence, loss aversion and herding. This is followed by chapter three, which is the literature review. This chapter is divided into two parts, evidence from China and evidence from US. The final chapter four summarizes the findings.

2 Theoretical Background

Market efficiency is a key concept in finance and economics. It refers to how well the market reflects available information in the asset pricing. If markets are efficient, prices react immediately and accurately to new information, both positively and negatively. In other words, the market behaves efficiently, prices are always "correct" reflecting the true value of the security. As a result, the principle of an efficient market is that excess returns are difficult to achieve without increased risk. Asset pricing is directly linked to efficient markets. It seeks to explain what determines prices, and how investors' risk appetite and market risks are reflected in prices.

Next, we look at two key financial theories that have been pillars of traditional finance: Efficient Market Hypothesis (EMH) and Capital Asset Pricing Model (CAPM). These theories provide a basis for understanding how behavioral finance challenges these traditional notions.

2.1 Efficient Market Hypothesis (EMH)

Economist Eugene Fama (1970) argues that the efficient market hypothesis means that security prices reflect all available information quickly and accurately. It means that rational investors use all available information to make decisions, and no single investor can constantly achieve above-average returns. However, according to Fama (1970), for a market to be efficient, it needs sufficient number of investors to have access to available information.

EMH is divided into three forms according to the type of information to which the market is expected to react efficiently. Weak form assumes that the market fully incorporates all historical price information. In semi-strong form assumes that market fully reflects all publicly available information such as announcements. The final form, strong form,

assumes that the market reflects all available information, including inside information which is relevant and could influence to price formation. (Fama, 1970).

Weak form tests show strong support, although the findings on the dependence of price changes do not provide sufficient evidence of market inefficiency. Semi-strong form tests also show support for the hypothesis, although the types of information examined are limited. In strong form tests have been found two deviations which show that there are investors which have monopolistic access to unpublished information. (Fama, 1970).

The efficient market hypothesis has also come in for a lot of criticism. Malkiel (2003) admits that market failures occur in the short term and are influenced by psychological factors. However, he argues that investors cannot reliably exploit market anomalies or patterns to obtain exceptional returns.

2.2 Capital Asset Pricing Model (CAPM)

The capital asset pricing model (CAPM) is a widely used financial theory and has been developed in the 1960s and has been independently presented by William Sharpe (1964) and John Lintner (1965), among others. They pointed out of the lack of a theory that accounts for risk in capital markets.

CAPM is a pricing model that explains the relationship between risk and expected return in capital markets. According to the CAPM, investors aim to maximize expected returns while minimizing risk, with higher expected returns achievable by taking on more risk (Sharpe, 1964). CAPM provides investors with an estimate of expected return, given an investment's risk level. CAPM formula can be present as following way:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f),$$

where $E(R_i)$ represents the expected return on asset i , R_f is the risk-free rate, β_i is the beta of the asset and $E(R_m)$ is the expected market return.

Investors make rational decisions based on expected returns and risk levels, with the aim of increasing returns and minimising risk. The key assumption of CAPM is that investors avoid risk. The investment decision can be divided into two parts according to the separation theorem of the model. The first part is determining the optimal ratio of risk-free to risky assets, which means that investors decide how much they want to invest in risk-free assets compared to risky assets. The second part is choosing the optimal mix of risky assets. Notably, for all investors the optimal mix of risky assets is the same, as investors need only focus on the ratio of risk-free to risky assets and not on the choice of different risky investments (Lintner, 1965).

Sharpe (1964) and Lintner (1965) identify other assumptions of the CAPM, which are simplifications of the real world: investors can borrow and lend at risk-free rates; the assumption is that there is a risk-free investment that provides a certain and stable return; all investors have the same time horizon, meaning that they make investment decisions over the same period; the markets are efficient, meaning all relevant information is reflected quickly in asset prices, and investors cannot take advantage of market inefficiencies to earn excess returns; investors have homogeneous expectations, meaning all investors agree on the expected return, risk, and correlations between different investments; there are no transaction costs or taxes, meaning investors can sell and buy assets without costs and taxes affecting investment decisions.

As already mentioned, these assumptions are simplistic, and the reality of how the market works is more complex and CAPM cannot take that into account. Nevertheless, the CAPM is a useful tool for investment analysis and risk management. Behavioral finance, however, offers a richer view of market dynamics by recognising psychological factors.

2.3 Behavioral Finance

Behavioral finance is a key area of research that incorporates insights from sociology and psychology. It investigates how psychological biases affect investors' economic decisions and consequently market outcomes. It has become better known among researchers since the 1990s. Behavioral finance considers the constraints of investor psychology and decision-making and thus challenges traditional theories like the Efficient Market Hypothesis and the Capital Asset Pricing Model, which were at the heart of the financial markets in the 1970s and to some extent even today. These traditional theories assume that individuals act rationally when making financial decisions and markets are efficient, while behavioral finance offers a broader multidisciplinary approach.

Two main pillars of behavioral finance are limits to arbitrage and cognitive psychology. Limits to arbitrage means challenges or constraints that prevent investors from taking advantage of market price errors. Mispricing can be divided into two categories. Recurring mispricing are short-term and capable of arbitrage. These are used by many investors as they can offer reliable returns. Since these mispricings are typically small, they do not create significant distortions, allowing the market to remain relatively efficient. The other category of mispricing is long-term, non-repeating. It may even be impossible to identify peaks and troughs of these mispricing at that moment. This is why investing too early can lead to significant losses. If investors withdraw money after a period of losses, this can increase buying and selling pressure. As a result, this exacerbates market inefficiencies and prevents market failures from being corrected. (Ritter, 2003, p. 430)

Cognitive psychology refers to the way individuals think about things and highlights the factors that contribute to people's systematic errors (Ritter, 2003). There are several psychological biases that affect investor behavior which can lead to irrational decision-making and therefore often impact market efficiency. Key biases include overconfidence, herding and loss aversion. By studying these biases, we can gain a better understanding of why people behave irrationally, how they affect market efficiency and asset pricing. In the following section, we will explore these three key biases in greater detail.

However, it is good to know at this point that psychological biases are not always the cause of market inefficiency. Incorrect pricing can be caused by short-term imbalances between supply and demand (Ritter, 2003). For example, technological developments or changes in market infrastructure can temporarily distort pricing, even in the absence of behavioral factors. Market failures can be more complex and multi-level.

2.3.1 Overconfidence

Overconfidence is well-known psychological bias, and it has been observed in many fields. Its definition is not unambiguous, and many researchers define it through its different manifestations, such as self-attribution and internal learning of the individual. In financial markets, overconfidence bias affects the way investors process and interpret the information available to them. Investors gather information about financial markets from a variety of sources, including news, analysis and rumours. These signals can be private or public. Investors' different interpretations and predictions of these signals lead to variations in market efficiency and pricing.

Odean (1998) states that investors tend to be overconfident about the accuracy of their own information. If investors believe in the accuracy of their information more than they should and underestimate other available information, such as historical data on asset returns, they will overweight their own information (Odean, 1998). In other words, investors may believe they know better than others or believe that their conclusions are correct, even if they are based on limited or incorrect information. By believing in the accuracy of their own information over reality, individuals also expect greater benefits than would be reasonable (Odean, 1998).

Daniel et al. (1998) find that overconfidence is more pronounced in tasks that require judgment, especially when feedback is delayed. This is because when individuals make decisions based on their own judgement, without immediate feedback to correct errors, they are more likely to overestimate their abilities. The lack of real-time information

makes it difficult to accurately assess the quality of decisions, which can lead individuals to believe that they are more skilled or knowledgeable than they really are. Additionally, individuals tend to have an inflated view of their own skills and often see themselves in a more positive light than others do (Daniel et al., 1998). This may be influenced by the personal nature of the task or issue, or the desire to maintain a positive self-image.

Self-attribution can lead to an increase in investor overconfidence. Individuals update their confidence based on the results of their biased decisions. If the information that becomes public is in line with the choices made, their confidence will increase. If the information that becomes public again contradicts the choices made, confidence will fall, but much less than in the case of the growth described above. Investors overreact to positive signals, which causes momentum in stock prices. As more public information becomes available later, prices will return to their true values. (Daniel et al., 1998).

Individuals learn about their own abilities over time by observing them and the consequences. When starting out, traders may be uncertain about their ability. With their first triumphant successes, they may mistakenly update their belief, believing it was due to their abilities rather than luck. This will boost overconfidence. However, as experience increases over time, this biased learning evens out and self-assessment becomes more realistic. (Gervais & Odean, 2021).

Overconfidence can be caused by many factors and has many definitions. The manifestations of overconfidence we discuss in this section, such as self-attribution and internal learning, show how this psychological bias can affect investor behavior. Understanding the role of overconfidence in financial decision making is crucial for improving market efficiency and asset pricing.

Overconfidence can lead to various market distortions, depending on who is overconfident. Odean (1998) presents three models of different types of traders to analyse the impact of overconfidence on the markets. The first type of investor is price takers.

Overconfident traders pay more attention to their own signals than those of others where trading is not based on optimal decisions. This can result in price distortions and increased trading. Also, it does not improve the expected utilities for traders.

The second type of investor are insiders. Overconfident insiders judge the private signal they receive as stronger, which leads to acting more aggressively than would be optimal and therefore increasing trading volume. Because they believe they are acting optimally but have misjudged the precision, it results in decreasing expected profits. However, overconfident insiders can earn higher profits under certain conditions. Market makers can set prices closer to real value when they notice the overconfidence of insiders, which leads to better quality of the price but also increases volatility (Odean, 1998).

The third type of investor are market makers, which includes traders who pay for the signal, traders who do not have that signal and noise traders. In this model, all traders consider the information available to be better than it is, but the difference is that some traders buy it, and others decide it is too expensive. This also explains why active managers may perform worse than passive ones, as they are too confident that they can beat the market and spend too many resources to do so. As a result, traders who bought the information have lower expected utility (Odean, 1998). This overconfidence, as described above, leads to market inefficiencies and price distortions.

2.3.2 Loss aversion

Loss aversion is a key psychological phenomenon that refers to an investor's tendency to place more emphasis on losses than on gains. This bias is particularly relevant in financial decision-making, as it often causes investors to avoid taking necessary risks, misjudge the potential of their investments, or underestimate the likelihood of adverse events.

Loss aversion has been presented for the first time as part of Kahneman and Tversky's (1979) prospect theory. They describe people as giving more weight to certain outcomes than to probable outcomes. In other words, they emphasise the chances of a sure profit,

even though risky alternatives could yield more profit. The reason for this decision is the uncertainty inherent in risky options. Similarly, for certain losses, individuals are willing to take more risk because they want to avoid the discomfort associated with uncertainty.

Similarly, Barberis et al. (2001) extends this idea by approaching it from two perspectives: investors are more sensitive to losses than to gains and investors' past experiences influence their loss aversion. The first perspective, sensitivity, refers to the asymmetry in how individuals experience losses and gains. Negative emotions caused by losing are stronger than positive emotions from winning (Kahneman & Tversky's, 1979). Also, a loss-averse investors need a higher premium to offset the risk of holding. This is why the volatility of return causes discomfort.

The other perspective, the influence of previous experiences, refers to the fact that previous experiences can shape their risk tolerance and thus future decisions. This means that past losses make investors more sensitive to future losses, while past gains increase their tolerance for potential future losses (Barberis et al., 2001).

In contrast to Barberis et al. (2001), who suggest that investors are more risk averse after previous losses, Gomez (2005) presents a different pattern, where investors avoid risk when there are gains and seek risk when there are losses. More specifically, this means that when investors are profitable, they may be less willing to take risky investments or sell profitable investments. On the other hand, when investors are at a loss, they may start taking more risks to "recoup" any losses. In other words, they can try to balance previous losses.

Definitions of loss-aversion discussed in this chapter highlights the complexity of loss aversion. Understanding these different reactions to risk is important for analysing how markets behave. These different reactions can affect market efficiency, as loss-averse behavior can lead to irrational decision-making. For example, as investors hold on to loss-

making investments or avoid beneficial risks, this can prevent the market from reflecting all available information.

Loss aversion affects market behavior and price formation. The impact of past profit losses on investors influences their future decisions, which can lead to irrational behavior. According to Gomes (2005) this also has an impact on asset demand and trading volumes. Surplus wealth has a significant role in investors' portfolio allocation behaviour, which refers to current wealth compared to a reference point.

When surplus wealth reaches a certain limit, loss-averse investors sell off stocks and use a portfolio insurance strategy to avoid losses. As stock prices rise, investors begin to balance the cost of avoiding losses with the cost of doing so, often leading them to sell a large part of their portfolio and lose out the equity premium. As prices continue to rise and surplus wealth increases, the cost of switching to the insurance rule is reduced, which means investors do not have to sell as many stocks. When the prices rise enough, investors switch the stocks. As a result, this leads to disposition effect, which means that investors have a greater tendency to sell winners and keep losers. (Gomes, 2005).

2.3.3 Herding

As a psychological phenomenon where investor decisions are guided by the decision of others, herding is an important part of behavioral finance. People have an innate ability to follow each other. Herding is part of our lives. It shows every day in many different sectors, such as neurology and sociology. Herding contradicts the assumptions of traditional financial theories about rational decision making. The herd behavior shows how a variety of factors, such as social influence, can lead to collective market behavior. Also, because many factors are involved, herd behavior is difficult to explain clearly.

Many researchers define herd behaviour in different ways. It often refers to behavior in which individuals adopt each other's patterns of behaviour. Herding can be divided to

individual and group aspects. From an individual perspective, for example, individuals may follow certain influential individuals or market leaders, while from a group perspective, they act as a group, driven by shared beliefs or prevailing market trends. Bikhchandani & Sharma (2000) share herd behavior into two parts: intentional herding and spurious herding.

Intentional herding refers to consciously making similar or identical decisions based on the decisions of other individuals. They may therefore consciously choose to follow the masses, thinking that this will lead to economic benefits. Investors and market participants who follow an intentional herd behaviour make risky decisions without assessing the real risks and benefits. (Bikhchandani & Sharma, 2000).

On the other hand, spurious herding can be described as a wandering pattern of behavior. Individuals may possess similar information and face similar decision-making problems and yet make similar decisions. The difference from intentional herding, as described above, is that they do not consciously make similar decisions. However, Bikhchandani & Sharma (2000) criticise this dichotomy and argue that many other factors influence decisions, for example different market conditions.

Avery & Zemsky (1998) argue that herd behaviour means that consumers act separately rather than simultaneously, which hampers the flow of information. Banerjee (1992) supports this argument for sequential decision-making. According to him, individuals observe past decisions made by others because they think their information is more useful. The result is that when individuals follow others, their decisions do not reflect their own knowledge and is all the less informative to those who follow them.

A similar explanation is arrived at by Bikhchandani et al. (1992), which explore the concept of an informational cascade. According to them, it happens when individuals choose to ignore their own knowledge or analysis and act on the actions of others, believing that they know better. Hence, once the cascade has started, the following approvals are

not informative. Individuals therefore harmonize their actions on the basis of limited information, creating a fragile equilibrium. Because initial decisions are made on the basis of limited information, even small changes in information or observations can cause significant changes in behavior. This can explain why, for example, booms and crashes emerge quickly and can be short.

Herding has an impact on price formation and market efficiency. When investors follow the decisions of others rather than basing decisions on their own information, price movements may be based more on social pressure than on well-founded information. Avery & Zemsky (1998) examine the relationship between herding behavior in financial markets and asset prices. Traders usually follow market trends based on their own information, but if there are uncertainties, these can lead to herd behavior. When one uncertainty is known to investors, such as a shock effect to an asset, this does not lead to herd behavior. Knowing the existence of a shock and its effect may lead to herd behavior, but it does not mean that it will affect price distortion. Add to this a third uncertainty factor, the quality of investor information, and it leads to a significant short-term pricing error through herd behavior. In other words, the amount of uncertainty is a key determinant of whether herd behavior occurs and whether it affects asset pricing.

3 Behavioral biases in China and US

In this chapter, we review previous research on how behavioral biases affect market efficiency and asset pricing in China and US financial markets. These regions form an interesting contrast because of their different cultural, economic and institutional characteristics. We seek to explore how the biases of overconfidence, loss aversion and herding manifest themselves and potentially affect market outcomes.

3.1 Evidence from China

Chen et al. (2007) study the overconfidence of Chinese investors, finding confirmation of this. They use data from 46,969 individual investors and 212 institutional investors' accounts, based on criteria relevant to the study. The survey covers the period 1998-2002.

To analyse overconfidence, Chen et al. (2007) estimate the degree of portfolio diversification and trading activity. They calculate the average monthly portfolio turnover of brokerage accounts and estimate diversification by the average number of stocks in the portfolio. First, Chen et al. (2007) point out that Chinese retail investors hold few stocks, on average 2.6 different types of stocks. This may be due to the fact that Chinese investors may have only one brokerage account. Institutional investors, on the other hand, hold an average of 15.5 shares.

Next, Chen et al. (2007) find that the average monthly portfolio turnover of Chinese retail investors is 27.3%, which is 327% per year, meaning that investors change a significant proportion of their holdings quite frequently. At this point, it is worth remembering that the average retail investor owns only 2.6 shares. This high turnover, combined with the low number of shares, may already point to the limited investment mentioned above. The study shows that institutional investors trade more than retail investors but also have better abnormal returns than retail investors. This could be explained by the fact

that institutional investors are so-called professionals in the market, which could be thought to be based, for example, on experience and better knowledge.

Chen et al. (2007) also find in their study that investors with older accounts on average own more stocks and trade more, which is a sign of overconfidence. These older accounts also perform better, which may be due to the fact that they are more diversified. However, larger accounts, which also own more shares and are more diversified, trade their shares more often and make worse returns. In other words, only larger accounts make worse returns. This suggests that the investment decisions of larger accounts may be based on overconfidence, which may lead them to underestimate risk and make less prudent investments.

As discussed earlier in the theory section of overconfidence, excessive trading can undermine investors' long-term returns. Huang et al. (2022) investigate what overconfidence has to do with trading volume in the Chinese stock market, finding strong evidence that it does. The study uses daily and monthly data on trading volumes of the Chinese A-share market from 2000 to 2020.

Huang et al. (2022) reveal that trading volume is associated with boom and bust cycles. In an upturn, trading volume increases faster, while in a downturn it decreases. They explain this pattern as indicative of overconfidence and self-attribution. In a boom, investors justify their profits on the basis of their own abilities and knowledge. This increases their motivation to trade even more. On the contrary, investors justify their losses by external factors beyond their control, which reduces their incentives to trade.

The impact of investors on the rapid growth of the market also triggers another irrational behavior, herding. Investors start to follow a trend in the market, which increases both returns and volume growth. However, while this behavior is irrational, the market eventually falls back to normal levels meaning that stock prices and trading return to normal. (Huang et al., 2022).

According to Huang et al. (2022) trading volume is positively correlated with lagged market returns. This means that if market returns have been positive in the previous period, trading volume is likely to increase in the next period. This finding may suggest that investors base their decisions in part on past market returns. They may feel confident and believe that the same trend will continue, leading to an increase in trading volume.

In addition, Huang et al. (2022) point out that investors' behavior and its impact on market trading volume can vary with the market capitalization. Smaller stocks are more price sensitive, but their trading volumes grow more slowly. Larger stocks are less sensitive to price changes, but their greater liquidity makes them easier to trade, so therefore trading volumes grow faster. Huang et al. (2022) highlight the dominance of smaller stocks by institutional investors. This means that the overconfidence of private investors is less likely to be reflected in smaller stocks. However, the results of this study by Huang et al. (2022) should be viewed critically because, as the authors point out, the study lacks variables that directly reflect investor overconfidence. Without direct measures, it is difficult to draw accurate conclusions.

Next, we move on to examine loss aversion in China. Jiang et al. (2021) investigate loss aversion among Chinese mutual fund investors, examining the accounts of over 300,000 investors from 2005-2011, finding strong evidence of loss aversion. The study dataset includes five hybrid funds from Chinese mutual fund companies that invest in equities and other assets with different weightings, but with equities as the main focus. They measure investor behavior by tracking the first sale and account liquidation afterwards.

Jiang et al. (2021) start by examining the disposition effect by looking at the proportions of winners and losers of sold investments. The results show that Chinese investors exhibit a loss aversion effect, with a higher proportion of sold funds being winning investments on average compared to sold losers. The study finds that, on average, the risk of loss is reduced by 78% across all five funds, suggesting that Chinese are less willing to

sell funds below the purchase price. This may be because investors want to hold on to loss-making investments in the hope that they will return to profit.

Jiang et al. (2021) add depth to the study by adding investor experience as a variable. They find that more experienced investors are not as loss averse as less experienced ones. For example, looking at a single fund, they find that the risk of selling a losing investment is reduced for less experienced investors, 56%, compared to 82% for more experienced investors. Experience therefore brings more knowledge to evaluate decisions and reduces irrational behaviour in terms of loss aversion.

Crises also destabilise investor behavior. Jiang et al. (2006) study the impact of a crisis on one of the funds before, during and after the crisis. The results suggest that the loss aversion of Chinese mutual fund investors peaks before the crisis and declines slightly during and after the crisis, while remaining statistically high. This behavior can be explained by the uncertainty and fear brought by crises, which irrationally affects investors' decision making.

Ao & Liang (2023) investigate market deviations in the Chinese stock market from the perspective of prospect theory, which includes loss aversion as a component. As a result, they show that loss aversion is observed in the Chinese market and plays a role in market behavior. The study uses monthly data from the CSI index of the Chinese stock market for the period 2010-2019 as the data set.

The study shows that prospect theory explains two-thirds of the anomalies in the Chinese market. The prospect theory highlights higher loss aversion and stronger decreasing sensitivity as specific contributing features. This suggests that Chinese investors are more sensitive to losses than to gains, a similar finding to that found by Jiang et al. (2006). Both of the studies on loss aversion discussed confirm that loss aversion exists in the Chinese market. Experience and market crises have a significant impact on investor behaviour.

As a final piece of evidence from China, we deal with herding. Fei & Liu (2021) study the impact of herd behaviour of Chinese investors on stock market volatility. In their study, they use the daily prices of listed A-shares on the Chinese stock market and the daily Fama and French factors from August 2005 to March 2021. They find strong support for the impact of herding behaviour on volatility fluctuations. It is noteworthy that the time period of the research includes three downturns, including the COVID-19 pandemic in 2020 onwards. This allows for research under different market conditions. Fei & Liu (2021) also show this by noting that the realized volatility of indices ranges from less than 10% to more than 100%.

To investigate how herding behavior affects volatility. Fei & Liu (2021) use direct herding measure, whereby herding can be divided into positive and adverse herding. Positive herding refers to the herding of investors towards the market portfolio, while adverse herding refers to herding away from the market portfolio. The study finds that positive herding occurs particularly during downturns and when it is strong, such as during the Chinese stock market turbulence in 2015-2016, followed by a longer period of adverse herding. As a result, herding is found to have an asymmetric effect on volatility fluctuations: positive herding increases market volatility, while adverse herding reduces it.

Moreover, Fei and Liu (2021) prove that the effect of herding on market volatility is unidirectional, meaning that market volatility does not directly affect herding behavior. The phenomenon found in the study may be explained by investors reacting more strongly to negative news, resorting to following other investors. Investors may also feel uncertain in times of market stress, when they may rely more on collective behaviour than on their own analysis. As markets calm down, investor behaviour may become less reactive.

Wang & Zao (2024) study how investors' herding behaviour asymmetrically affects price bubbles in stock markets in China. They use daily data from the Shanghai Stock Exchange for the period 1.1.2004-30.6.2022. Like the sample period in the study by Fei & Liu (2021),

the time frame of Wang & Zao's (2024) research also includes both boom and bust cycles, enabling the consideration of different market conditions.

Wang & Zao (2024) observe that investor herding affects price bubbles differently depending on market conditions, with the impacts being asymmetric in both the short and long term. In boom periods, herding behavior and bubbles have a strong positive correlation. An increase in herding behavior contributes to bubble formation, while a decrease in herding can help mitigate the expansion of the bubble. In downturns, the negative correlation is stronger. Increased herding behaviour can accelerate bubble collapse, while reduced herding behaviour has no inhibitory effect on bubble collapse.

Figure 1. illustrates the dynamic relationship between herd behavior of investors and stock market bubbles. From the graph, we can see that the price bubble index and price change trends are aligned. When a bubble grows rapidly, the herding behavior index also rises significantly. When a bubble bursts, prices fall, but the herding behavior index still remains high. The herding behavior index only starts to fall slowly when the bubble starts to flatten out.

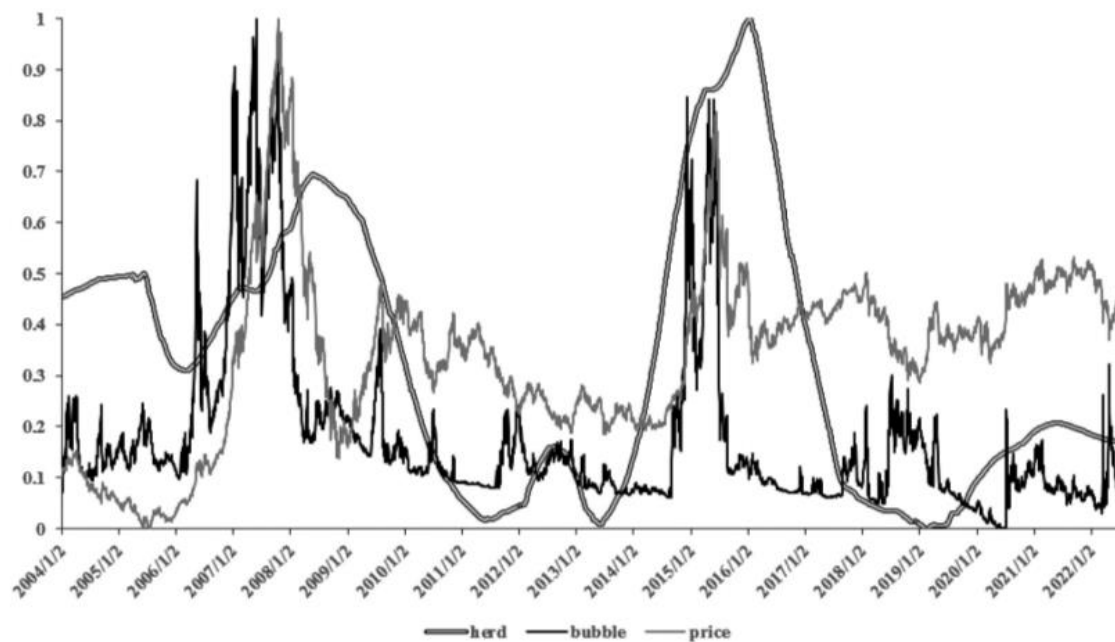


Figure 1. Relationship between herding behavior index, price bubble index and stock market prices. (Wang & Zhao, 2024)

There are many reasons why investors follow the decisions of others, including the uncertain times that has been mentioned earlier. People rely more on the analyses of others and may ignore their own data, for example because of greed in a boom or fear in a downturn. As Bikhchandani & Sharma (2000) report, individuals may consciously follow the masses, hoping to gain economic advantage.

3.2 Evidence from the US

Bouteska et al. (2023) study overconfidence and its impact on stock market inefficiency, specifically analysing the causal relationship between returns and trading volume. Using SP&500 daily closing prices and trading volume data for the period 2016-2021, they show through their study that US investors have overconfidence when trading the S&P500 index.

Bouteska et al. (2023) find in their study asymmetric responses of trading volume to return shocks by return regime, suggesting investor overconfidence. Trading volume first reacts negatively to yield shocks, then turns positive in the following days in a low return scenario. In the high return scenario, trading volume increases sharply immediately after a shock to returns. They also find that reactions to yield shocks persist, suggesting that investor overconfidence is persistent in the US.

The asymmetric response described above can undermine market efficiency, as it can create unrealistic price movements, even though the study shows that the increase in trading volume does not cause significant fluctuations in returns. Bouteska et al. (2023) point out that this type of reaction may also be due to an increase in investors, which has not been taken into account in their study.

Chuang & Lee (2006) also confirm the presence of overconfidence among US investors. They investigate the effects of overconfidence by examining the overall behavior of investors. The study data include stocks listed for at least 4 years on the NYSE and AMEX

exchanges from 1963 to 2001, with data available on stock price, trading volume, and market value.

First, Chuang & Lee (2006) explore the link between overconfidence and its reaction to private information and public information. Stock prices overreact to private information as measured by both value-weighted prices and equilibrium prices. However, the correction is much steeper for weighted prices. On the contrary, stock prices underreact to public information, both with weighted prices and equilibrium prices. Weighted prices recover quickly, i.e. it is a short-term effect. Balanced prices take longer, suggesting a slower reaction time for small firms. As discussed earlier in the theory section, investors can be overconfident about the accuracy of their own information, which may lead them to underestimate other available information. As a result, short-term as well as long-term price distortions can be observed in the US market.

Second, Chuang & Lee (2006) examine overconfidence and trading volume. Specifically, they investigate whether market gains or losses affect overconfident investors by increasing or decreasing trading volume. They find that past returns are strongly associated with future trading volumes, but no other way around. The study also finds that overconfidence is evident in both down and up markets, but the signs are stronger in up markets. This may be because investors who are overconfident in up markets may believe that their success is due to their own skills rather than to the general rise in the market. If they see significant returns in their portfolio, they may become more confident and increase their trading volume in anticipation of more returns.

Third, Chuang & Lee (2006) study the relationship between overconfidence and volatility. The study again confirms the existence of overconfidence in the US and that it has at least a partial impact on market volatility. They also test the leverage effect, which shows that losses increase volatility more than gains. This may suggest that overconfident investors who have overestimated their own abilities and forecasts are more prone to react to negative market movements.

Finally, Chuang & Lee (2006) examine how overconfidence affects risk taking. Their study suggests that overconfident investors who have experienced market gains may overestimate their skill, resulting in higher risk taking. This manifests itself in them trading more aggressively in higher-risk stocks, expecting to reap even better profits.

Next, we look at the evidence of loss aversion. Haigh & List (2005) investigate the myopic loss aversion behavior of professional traders by comparing them to an experimental control group of students who have already been shown to exhibit this behavior in previous studies. In other words, the study aims to examine how real professional market participants with practical experience and a deeper understanding of market dynamics differ from the control group. Haigh & List (2005) find a surprising result that professional investors seem to exhibit more myopic loss aversion than students. However, it should be noted that the study is based on observational comparisons of student behavior, and thus the effects observed in their study may not correspond to behavioral patterns found in a natural market environment.

Haigh & List (2005) state their research finding to be important for professional traders as being an influential factor in the price formation process in the market. Coval & Shumway (2005) show the existence of loss aversion, and that loss aversion affects market prices. Their study is based on market makers whose trade with government bond futures contracts at the Chicago Board of Trade. The study analyses the change in traders' behavior by dividing the trading session into two parts, morning and afternoon.

Coval & Shumway (2005) find first a significant difference based on morning trading results. Traders who make losses in the morning take more risk in afternoon trading by making more and larger trades and tend to make more price-setting trades. In addition, traders with large positions after morning increase risk to rebalance their holdings. This behaviour is contrary to traditional financial theory.

Investors tend to compensate for their losses by taking more risk, although this does not necessarily lead to higher expected returns and risk-adjusted returns may even be lower. This also turns out to be the case in a study by Coval & Shumway (2005), where morning losing traders have lower afternoon returns than morning winning traders.

As previously mentioned, the study by Coval & Shumway (2005) shows that traders' loss aversion affects market prices. They examine this by comparing the price of a trade to the price of the previous trade. If someone buys at the ask price and the price rises, or if someone sells at the bid price and the price falls, they classify this as a price-setting trade. According to the study, traders who incurred losses in the morning engage in up to 25% more price-setting trades in the afternoon than traders who made profits in the morning.

However, even if these traders manage to influence prices, the price changes are not permanent but short-term, as other traders try to correct the situation (Coval & Shumway, 2015). This suggests that traders who take on more risk in an attempt to recoup their losses end up paying a high price, as counteractions by other traders lead to larger price fluctuations and potentially greater losses-

Loss aversion may also have an impact on volatility in the US. Coval & Shumway (2015) report in their study that traders who are loss averse in the morning contribute to the increase in afternoon volatility in the short term, but the effect fades quickly. This rapid market correction may indicate, as mentioned earlier, the reaction of other markets in recognizing loss-induced behavior.

Finally, let us consider observations on herding from prior literature on US markets. Galariotis et al. (2015) examine the prevalence of herd behavior in the US using daily S&P 100 prices as data. The data period is 1989-2011, which includes both up and down days. As a result, they find that there is a herding tendency towards market consensus. In other words, US herding behavior is information-driven, and investors herd in response to the release of macroeconomic information. However, it is worth noting that

when testing for herding behavior using all stocks in the S&P 100 and dividing them into four subsamples—value, growth, small, and large stocks—no evidence of herding was observed.

In one test, Galatoris et al. (2015) find increased herding on days with significant macroeconomic news releases. They observe that herding occurs in all stocks except growth stocks. This result suggests that the market reacts strongly to macroeconomic news, but growth stocks behave differently. This difference may be due to their more volatile nature or investor expectations regarding their long-term potential.

In another test, Galatoris et al. (2015) find that in times of crisis, herding in the US market spills over to other markets. This result is interesting because it shows that markets can be interconnected, especially during economic crises. Investors in other markets may follow and react to movements in US markets, creating uncertainty in other regions, which may lead to similar reactions.

The last purpose of test by Galatoris et al. (2015) is to examine herding behavior during crises more closely by distinguishing between fundamental-driven and non-fundamental-driven herding, using all four subsamples of stocks. Before splitting they do a test with selected crisis and find herding behavior only during Subprime crisis. After the split, herding behavior is still observed during the Subprime crisis, but also during the Asian and Russian crises. As a conclusion, they state that the herding behavior during the Subprime crisis was non-fundamental, meaning investors reacted with irrational behavior, such as interpreting market sentiment. The herding behavior during the Asian and Russian crises is based on fundamental-driven behavior.

The results of a study by Choi & Skiba (2015) confirm the idea that herding is based on fundamental factors. According to their study, institutional herding is evident in the United States, which is significant both statistically and economically. The study uses

institutional ownership data and focuses specifically on herding behavior at the portfolio level, excluding domestic holdings.

Choi & Skiba (2015) test whether institutional herding stabilises prices. They find that institutional demand has little impact on future returns and is positively correlated with current returns of securities. This implies that fundamental factors are the underlying reasons for institutional herding, meaning that information is incorporated into the prices of securities. Such herding is unintentional and contributes to more efficient markets (Choi & Skiba, 2015).

4 Conclusion

This thesis examines behavioral biases and their impact on market performance, particularly in the Chinese and US markets. The study focuses on overconfidence, loss aversion and herding. The analysis suggests that these psychological factors undermine market efficiency and affect investors' decision-making differently in these two market areas.

In both markets, overconfidence exists. Overconfidence affects markets differently in China and the US because of investor behavior and institutional differences. Chinese investors trade actively, own few stocks and trade frequently, which indicates overconfidence. In upturns, they increase trading, believing that profits are due to their own skill, while in downturns they decrease trading, blaming losses on external factors. In the US, overconfidence is reflected in asymmetric reactions to market shocks, overreacting to private information and underreacting to public information, causing price distortions. In upturns, US investors take more risk, which increases volatility and trading

Loss aversion is also evident in China and the United States. In China, studies show that investors are more sensitive to losses than to gains, which is reflected in their reluctance to sell loss-making investments. However, more experienced investors are less likely to make irrational decisions. Crises also have an impact in China. Loss aversion is particularly strong during market shocks, but more experienced investors somewhat offset the effects. In the US, similar findings are found for both professional market participants and less experienced ones, but professional investors show even greater loss aversion. The effects of loss aversion are reflected in market price formation. Loss-making traders tend to compensate for their losses by taking more risk, even though this may lead to lower long-term returns. The behavior of these investors can increase volatility in the short term and affect market prices.

Lastly, herding, which has also been observed in both markets. In China, herding affects market volatility in such a way that positive herding increases volatility, especially in downturns, while adverse herding reduces it. Herding also contributes to the emergence

of price bubbles in booms and accelerates their bursting in downturns. In the US market, herd behaviour is mainly information- and fundamentals-driven. Investors react strongly to macroeconomic news, leading to herd behavior oriented towards market consensus. In times of crisis, herding intensifies and can spread to other markets, suggesting that investors follow US market movements and adjust their behaviour accordingly.

Based on the literature reviewed, all three behavioral biases, overconfidence, loss aversion and herding are observed among investors in both markets in China and the US. Both institutional and retail investors are subject to these behavioral biases. Therefore, the first hypothesis is supported.

A review of the literature also confirms that behavioral biases affect these two areas differently. In China, overconfidence is reflected in frequent trading and strong reactions to market trends, while in the US it is reflected in asymmetric reactions to market shocks. Loss aversion influences decision-making in both markets, with Chinese investors reluctant to sell loss-making assets, while in the US professionals are even more loss averse and sometimes increase risk-taking to correct losses. Herding behavior is also different: in China it is driven by price bubbles and increased volatility, while in the US it is primarily driven by macroeconomic news and intensifies during crises. These differences are aligned with cultural, economic and structural factors, supporting the second hypothesis that behavioral biases are identified or observed differently across the two markets.

For future research, this thesis suggests more research into behavioral finance and behavioral biases in different markets. Differences in methodology also hinder the interpretation of evidence from prior studies. Use of similar methods in future research would make it possible to better compare differences and similarities between regions, which could help to understand the factors that influence behavioral biases.

References

- Adaramola, A. O., Kayode, P. A., Adewale, O. V., & Ogiamien, O. F. (2022). Behavioural finance: An exploratory review. *The Journal of Economic Research & Business Administration*, 142(4). <https://doi.org/10.26577/be.2022.v142.i4.04>
- Ao, Z., Ji, X., & Liang, X. (2023). Can prospect theory explain anomalies in the Chinese stock market? *Finance research letters*, 58, 104466. <https://doi.org/10.1016/j.frl.2023.104466>
- Avery, C., & Zemsky, P. (1998). Multidimensional Uncertainty and Herd Behavior in Financial Markets. *The American economic review*, 88(4), 724-748.
- Banerjee, A. V. (1992). A Simple Model of Herd Behavior. *The Quarterly journal of economics*, 107(3), 797-817. <https://doi.org/10.2307/2118364>
- Barberis, N., Huang, M., & Santos, T. (2001). Prospect Theory and Asset Prices. *The Quarterly journal of economics*, 116(1), 1-53. <https://doi.org/10.1162/003355301556310>
- Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *The Journal of political economy*, 100(5), 992-1026. <https://doi.org/10.1086/261849>
- Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF staff papers*, 47(3), 279-310. <https://doi.org/10.2307/3867650>
- Bouteska, A., Harasheh, M., & Abedin, M. Z. (2023). Revisiting overconfidence in investment decision-making: Further evidence from the U.S. market. *Research in international business and finance*, 66, 102028. <https://doi.org/10.1016/j.ribaf.2023.102028>

- Chen, G., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of behavioral decision making*, 20(4), 425-451. <https://doi.org/10.1002/bdm.561>
- Choi, N., & Skiba, H. (2015). Institutional herding in international markets. *Journal of banking & finance*, 55, 246-259. <https://doi.org/10.1016/j.jbankfin.2015.02.002>
- Chuang, W., & Lee, B. (2006). An empirical evaluation of the overconfidence hypothesis. *Journal of banking & finance*, 30(9), 2489-2515. <https://doi.org/10.1016/j.jbankfin.2005.08.007>
- Coval, J., & Shumway, T. (2005). Do Behavioral Biases Affect Prices? *The Journal of finance (New York)*, 60(1), 1-34. <https://doi.org/10.1111/j.1540-6261.2005.00723.x>
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance*, 53(6), 1839–1885. <https://doi.org/10.1111/0022-1082.00077>
- Dolder, D., & Vandenbroucke, J. (2024). Behavioral risk profiling: Measuring loss aversion of individual investors. *Journal of banking & finance*, 168, 107293. <https://doi.org/10.1016/j.jbankfin.2024.107293>
- Fama, E. F. (1970). EFFICIENT CAPITAL MARKETS: A REVIEW OF THEORY AND EMPIRICAL WORK. *The Journal of Finance*, 25(2), 383–417. <https://doi.org/10.1111/j.1540-6261.1970.tb00518.x>
- Fei, T., & Liu, X. (2021). Herding and market volatility. *International review of financial analysis*, 78, 101880. <https://doi.org/10.1016/j.irfa.2021.101880>

- Feng, Y. (2001-06-01). Political Freedom, Political Instability, and Policy Uncertainty: A Study of Political Institutions and Private Investment in Developing Countries. *International studies quarterly*, 45(2), 271-294. <https://doi.org/10.1111/0020-8833.00191>
- Galariotis, E. C., Rong, W., & Spyrou, S. I. (2015). Herding on fundamental information: A comparative study. *Journal of banking & finance*, 50, 589-598. <https://doi.org/10.1016/j.jbankfin.2014.03.014>
- Garcia, F., Mendez, D., Ellis, C., & Gautney, C. (2014). Cross-cultural, values and ethics differences and similarities between the US and Asian countries. *Journal of technology management in China*, 9(3), 303-322. <https://doi.org/10.1108/JTMC-05-2014-0025>
- Gervais, S., & Odean, T. (2001). Learning to Be Overconfident. *The Review of financial studies*, 14(1), 1-27. <https://doi.org/10.1093/rfs/14.1.1>
- Gomes, F. (2005). Portfolio Choice and Trading Volume with Loss-Averse Investors. *The Journal of business (Chicago, Ill.)*, 78(2), 675-706. <https://doi.org/10.1086/427643>
- Haigh, M., & List, J. (2005). Do Professional Traders Exhibit Myopic Loss Aversion? An Experimental Analysis. *The Journal of finance (New York)*, 60(1), 523-534. <https://doi.org/10.1111/j.1540-6261.2005.00737.x>
- Huang, J., Wang, Y., Fan, Y., & Li, H. (2022). Gauging the effect of investor overconfidence on trading volume from the perspective of the relationship between lagged stock returns and current trading volume. *International finance (Oxford, England)*, 25(1), 103-123. <https://doi.org/10.1111/infi.12405>

- Jiang, J., Shrider, D. G., Ting, H., & Wu, Y. (2021). Are mutual fund investors loss averse? Evidence from China. *The Financial review (Buffalo, N.Y.)*, 56(2), 231-250. <https://doi.org/10.1111/fire.12252>
- Li, W., Rhee, G., & Wang, S. S. (2017) Differences in herding: Individual vs. institutional investors. *Pacific-Basin finance journal*, 45, 174-185. <https://doi.org/10.1016/j.pacfin.2016.11.005>
- Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The review of economics and statistics*, 47(1), 13-37. <https://doi.org/10.2307/1924119>
- Liu, H., Chuang, W., Huang, J., & Chen, Y. (2016). The overconfident trading behavior of individual versus institutional investors. *International review of economics & finance*, 45, 518-539. <https://doi.org/10.1016/j.iref.2016.07.016>
- Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2), 263-291. <https://doi.org/10.2307/1914185>
- Malkiel, B. G. (2003). *The Efficient Market Hypothesis and Its Critics*.
- Odean, T. (1998). Volume, Volatility, Price, and Profit When All Traders Are Above Average. *The Journal of Finance*, 53(6), 1887–1934. <https://doi.org/10.1111/0022-1082.00078>
- Ritter, J. R. (2003). Behavioral finance. *Pacific-Basin finance journal*, 11(4), 429-437. [https://doi.org/10.1016/S0927-538X\(03\)00048-9](https://doi.org/10.1016/S0927-538X(03)00048-9)
- Scharfstein, D. S., & Stein, J. C. (1990). Herd Behavior and Investment. *The American Economic Review*, 80(3), 465–479. <http://www.jstor.org/stable/2006678>

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance* 19:3, 425-442.

Wang, Y., Yu, C., & Zhao, X. (2024). The asymmetric effect of investor herding on the asset price bubble - evidence from the Chinese stock market. *Applied economics*, 1-14. <https://doi.org/10.1080/00036846.2024.2319651>

Yue, P., Fan, Y., Batten, J. A., & Zhou, W. (2020). Information Transfer between Stock Market Sectors: A Comparison between the USA and China. *Entropy (Basel, Switzerland)*, 22(2), 194. <https://doi.org/10.3390/e22020194>

Zhang, D., Lei, L., Ji, Q., & Kutan, A. M. (2019). Economic policy uncertainty in the US and China and their impact on the global markets. *Economic modelling*, 79, 47-56. <https://doi.org/10.1016/j.econmod.2018.09.028>