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Risk perception, behavioral bias, and excessive trading: Evidence from investor-level data in China during the COVID-19 pandemic

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ABSTRACT

To investigate the "excessive trading puzzle", we develop a structural equation model featuring a moderation effect of risk perception and a mediation effect of behavioral bias. Based on a comprehensive survey conducted in China during the COVID-19 pandemic, we distinguish among four types of behavioral bias: overconfidence, risk-seeking, disposition effect, and sensation-seeking. We find that the moderation effect is consistently present, while the mediation effect is only significant for overconfidence and risk-seeking. The relationships demonstrate spatial heterogeneity and temporal variation, emphasizing the importance of localized and evolving regulations in maintaining financial stability.

1.Introduction

In the evolving landscape of financial markets, the interplay between behavioral biases and trading behaviors remains an intriguing field of investigation[1,2]. Specifically, the so-called "excessive trading puzzle", initially observed in the US market by Odean[3] and Barber & Odean[4], has attracted much research interest in recent literature of behavioral finance[5]. The puzzle is embodied by underperformance relative to the market index before fees, exacerbated performance due to transaction costs, and worse outcomes for those who trade more frequently. Existing literature suggests multiple behavioral explanations, such as overconfidence[6], realization utility[7], disposition effect[8], risk-seeking or gambling preference[9], sensation-seeking[10], social interaction[11], and low financial literacy[12]. However, empirical importance of these mechanisms is subject to spatial heterogeneity and temporal variation, so research needs to be updated on a regular basis for different markets in different times[13,14]. Our study fills the gap of the Chinese market during the COVID-19 pandemic.

The connection between behavioral biases and excessive trading has implications for both investors and policymakers. On the one hand, cognitive and emotional factors can lead to over-trading and under-diversification for retail investors at the individual level, thereby hampering the financial health of an investor[15]. On the other hand, "collective animal behaviors" can lead to bubbles at the aggregate level, posing a threat to the financial stability of a country[16,17]. Studies in this field usually adopt purely theoretical models[18] or secondary data research[19]. However, it is difficult to empirically identify the effects of behavioral biases from secondary observational data. One solution is to utilize experiments[20], while evidence from controlled experiments may face the validity challenge[21]. Another straightforward solution is to use surveys, but most primary data are small scaled (typically hundreds) which brings about the generalizability concern[22,23] as well as framing issues[24].

To address the empirical challenge, this study aims to investigate the structural relationships among risk perception (RP), behavioral bias (BB), and excessive trading (ET) based

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on a comprehensive survey conducted in China during the COVID-19 pandemic. The carefully designed questionnaire enables us to quantify abstract concepts like RP and BB, so empirical identification of causes and effects of these conceptual constructs is possible. Moreover, the survey was led by the regulatory body China Securities Regulatory Commission (CSRC), which ensures the reliability and representativeness of the data (more than 30,000 investors). As a result, it combines the advantages of primary data (flexible design) and secondary data (large scale). The high-quality data source constitutes the first contribution of the research.

The second contribution of our paper is theoretical. Building on behavioral finance theories, we have developed a structural equation model among RP, BB, and ET. The structural model features a moderation effect of RP on the BB-ET relationship and a mediation effect of BB on the RP-ET relationship. The premise of this research lies in the recognition that RP is a foundational determinant of financial decision-making. Investors' subjective assessments of risk play a pivotal role in shaping their strategies, asset allocations, and trading frequencies. As a bridge between RP and ET, various forms of BB can lead individuals away from the path of perfect rationality in the form of cognitive shortcuts and decision-making heuristics.

By capturing real-world insights from market participants, the third contribution of this paper is to bridge theoretical understanding and practical decision-making. The rich dataset on individual investment behaviors enables us to open the "black box" of decision processes of retail investors. The nuanced analysis provides valuable insights for both financial professionals and policymakers. The unique circumstances brought about by the COVID-19 pandemic provide a valuable sample period to explore how market participants respond to heightened uncertainties and the psychological impact of the crisis on their trading behavior. Specifically, China's financial markets, being one of the largest and most dynamic globally, witnessed significant fluctuations during the pandemic, reflecting the broader economic and societal challenges posed by the virus. China's experience during the pandemic serves as a microcosm of global financial markets. The rapid spread of the virus, coupled with unprecedented policy responses, created an environment ripe for studying how risk perception evolves and how it influences trading decisions.

Based on the two-wave survey in China, this paper arrives at the following three key findings. First, it confirms a moderation effect of RP on the BB-ET relationship, but the mediation effect of BB on the RP-ET relationship is not significant for the overall measure of BB. Nevertheless, when refined measures of BB are used, significant mediation effects emerge for overconfidence bias and risk-seeking bias. Second, spatial heterogeneity exists across different regions. The western provinces tend to have a stronger mediation effect but a weaker moderation effect. Third, temporal variation is found across different stages of the pandemic. As the pandemic approaches the end, both mediation effects and moderation effects of RP grow stronger. These empirical findings are based on a structural model which can address the self-selection bias due to endogeneity of BB.

In the next section, we briefly review the literature related to RP, BB, and ET, building on which we develop three sets of testable hypotheses. The hypotheses are integrated into a unified conceptual framework. Section 3 discusses the data and the structural equation model to empirically operationalize the conceptual framework. Section 4 presents the baseline results of the model, and section 5 evaluates spatial heterogeneity and temporal variation of the findings. Section 6 concludes with policy implications.

2.Literature Review and Hypotheses Development

The foundation of the heuristics and biases literature originates from the concept of bounded rationality, as proposed by Simon[25]. This theory posits that humans aspire to make rational decisions, yet they grapple with constrained cognitive resources and time limitations, hindering the pursuit of optimal choices. Under these constraints, individuals often adopt cognitive shortcuts or heuristics as a means of conserving mental effort[26].

Various psychological mechanisms have been identified as contributors to behavioral biases in investment. For example, ambiguity aversion and a preference for familiarity have been linked to a reluctance to diversify[27]. Excessive trading has been associated with overconfidence and sensation-seeking[28], while the hesitation to realize losses is influenced by loss aversion and mental accounting[29]. The tendency to extrapolate past returns excessively is related to representativeness and the hot hands fallacy[30], and skewness preferences can be explained by cumulative prospect theory[31]. Cronqvist & Siegel[32] find that biases are manifestations of innate and evolutionary ancient features of human behavior.

Following these theoretical advancements, empirical literature has provided rich evidence for various forms of behavioral biases. A similar study is Phan et al.[15] who use survey to study over-trading and under-diversification of retail investors in Vietnam. More recently, it is found that the COVID-19 pandemic can attenuate the manifestation of the disposition effect in China[33]. Following the theoretical and empirical literature reviewed above, we hypothesize a RP-BB relationship:

[H1] Investors' levels of RP can influence their BB.

Thanks to the flexibility of the questionnaire design, we can further explore different types of biases. It greatly enriches what can be said about the mechanisms of how behavioral biases affect excessive trading. We distinguish four popular types of behavioral bias: (a) overconfidence bias (over-estimation of asset values in the investment test, (b) disposition bias (stopping loss too late or taking profit too soon), (c) risk-seeking bias (preferences over high-risk, high-return investments), and (d) sensation-seeking bias (preferences over newly issued stocks). Therefore, [H1] can take the following four forms.

[H1a] Investors' levels of RP affect investors' BB towards overconfidence bias.

[H1b] Investors' levels of RP affect investors' BB towards risk-seeking bias.

[H1c] Investors' levels of RP affect investors' BB towards disposition bias.

[H1d] Investors' levels of RP affect investors' BB towards sensation-seeking bias.

Excessive trading, characterized by frequent and often impulsive buying and selling of financial instruments, has been a subject of considerable interest within behavioral finance[34]. The literature has identified many mechanisms by which behavioral bias can affect excessive trading. For example, overconfidence bias, rooted in the tendency to overestimate one's own abilities, is linked to heightened trading activity and volatility[35]. If investors are overconfident, they overweight their own private information at the expense of ignoring publicly available information[36,37]. As a result, investors overreact to private information and underreact to public information, and this asymmetric response of overconfident investors induces short-horizon momentum and long-horizon reversal in stock returns[38]. Similarly, risk-seeking bias involves a tendency for individuals to prefer riskier options over safer ones, often driven by a desire for excitement and thrill[5]. This bias can lead investors to engage in actions that maximize risk exposure, including excessive trading and beta herding[39]. In addition, micro level risk-seeking behavior may lead to a cascading effect, influencing others to adjust their trading strategies, contributing to excessive trading at the macro level[16]. These two types of biases tend to increase the tendency of excessive trading.

In contrast, the disposition effect, where investors with fear of realizing losses tend to hold on to losing investments for too long[8]. It can reduce excessive trading or even normal trading[40]. Sensation-seeking bias reflects a psychological tendency wherein individuals actively seek novel and stimulating experiences, often driven by a desire for excitement and arousal[41]. Studies suggest that individuals with a high sensation-seeking bias may be prone to engaging in over-trading[42]. However, investors seeking constant excitement may also avoid trading when market conditions become perceived as dull or unstimulating, leading to a reluctance to engage in necessary portfolio adjustments[43]. Sensation-seeking behavior can contribute to increased market volatility, as these investors actively react to perceived opportunities for excitement, influencing overall market sentiment. Based on the review above, we establish the following hypotheses on the BB-ET relationship:

[H2] Investors exhibiting BB can affect the tendency of ET.

[H2a] Investors exhibiting BB towards overconfidence bias can affect the tendency of ET.

[H2b] Investors exhibiting BB towards risk-seeking bias can affect the tendency of ET.

[H2c] Investors exhibiting BB towards disposition bias can affect the tendency of ET.

[H2d] Investors exhibiting BB towards sensation-seeking bias can affect the tendency of ET.

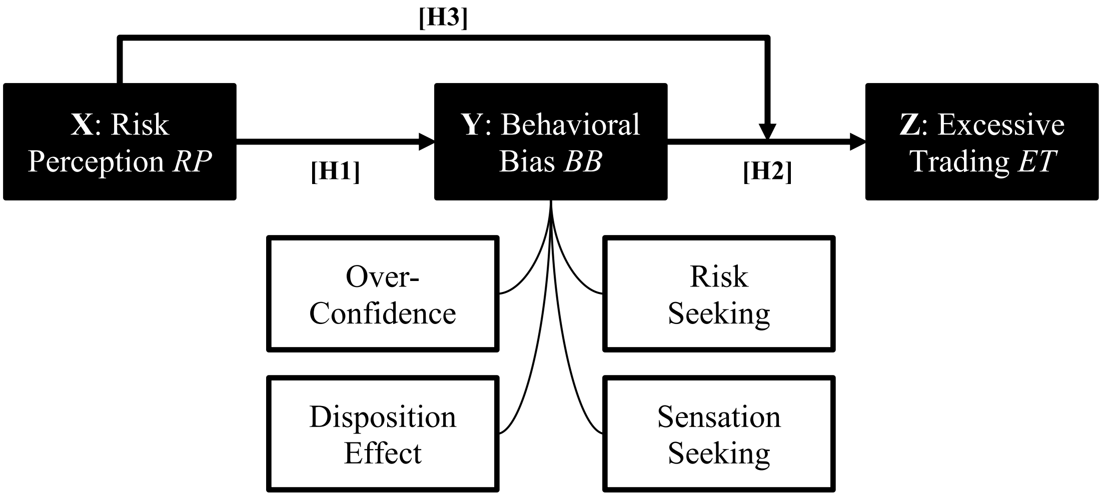

Fig 1. The Conceptual Framework and Hypotheses

Moreover, behavioral biases can lead to impulsive, suboptimal trading decisions that deviate from rational and well-informed strategies, and this effect can be moderated by cognitive and emotional factors, shaping how investors interpret and respond to risks. For example, investors with higher risk perception may be more influenced by loss aversion, leading to heightened caution and potentially mitigating excessive trading tendencies associated with this bias[8]. High-risk perception individuals may exhibit greater caution even if being overconfident, which can mitigate impulsive trading decisions typically associated with overconfidence[44]. Investors with varying levels of risk perception may exhibit different trading patterns in response to affect[45]. Based on the literature, we formulate the following hypotheses to capture the moderation effect of risk perception on the BB-ET relationship.

[H3] Investors' levels of RP can moderate the effects of BB on ET.

[H3a] Investors' levels of RP can moderate the effect of overconfidence bias on ET.

[H3b] Investors' levels of RP can moderate the effect of risk-seeking bias on ET.

[H3c] Investors' levels of RP can moderate the effect of disposition bias on ET.

[H3d] Investors' levels of RP can moderate the effect of sensation-seeking bias on ET.

To summarize, we use Figure 1 to demonstrate the conceptual framework among the three hypotheses, where the four types of BB lead to variants of the model. Essentially, [H1] and [H2] make BB a mediation effect, while [H3] makes RP a moderation effect. In most empirical studies, hypotheses are tested separately despite obvious endogeneity issues in one or more key variables. In our case, it is easy to see that behavioral bias is not randomly, but endogenously determined. To accurately capture the interdependent relationships among the three variables (RP, BB, and ET), a structural equation model is needed to operationalize the sophisticated conceptual framework in Figure 1.

3.Empirical Strategy

This section discusses our empirical strategy including data collection and model specification. Data availability determines model feasibility. Therefore, we begin the section with data description before delving into the structural equation model.

3.1.Data

The data were sourced from online questionnaire surveys by an authoritative organization in China. The survey managed to recruit tens of thousands of respondents, making it superior in sample size to private surveys (e.g., about a thousand in Choi & Robertson[46]). The sample covers almost all provinces and in two waves (June 2020 and June 2022). The survey explored the behavioral and decision-making habits of Chinese stock market investors, encompassing socio-demographic features (respondents' age, occupation, education, etc.), financial asset holdings (stocks, real estate, investable assets, etc.), investment preferences (investment styles, holding periods, etc.), subjective attitudes towards investment (risk attitudes, psychological characteristics, etc.), and financial literacy. The data provide essential support for studying the investment behavior of Chinese investors in the stock market.

The survey exhibits nationwide representativeness. It covers 30,002 stock market investors across 31 provinces and municipalities in China. The survey was designed considering different geographical locations, age groups, account sizes, asset sizes, and investment experience. To enhance the representativeness of the survey sample, the questionnaire leveraged 14 major securities firms and one financial regulatory institution nationwide. The survey was conducted through online links, enabling respondents to conveniently complete the questionnaire by scanning QR codes. Typically, a questionnaire could be completed within 10 minutes. Institutional efforts were made to actively encourage participation from diverse demographic groups to ensure a sufficiently rich sample.

Thanks to the authoritative support, the data demonstrate reliability and consistency with real market performance. To ensure the quality of the questionnaire sample, various methods were employed, including pre-survey preparations (on-site visits to securities firms, investment consultants, and stock traders for questionnaire design), process supervision (QR codes link distribution and quality monitoring), and post-survey auditing (data auditing and outlier handling). Additionally, for accuracy assurance, during the quality control and cleaning of the collected sample, samples with unusually short average question completion times (average duration less than 3 seconds per question) or low variability in completion times between questions (standard deviation of duration less than 2.5 seconds) were excluded. Consistency checks were performed based on questionnaire context to identify and exclude samples with contradictory responses (e.g., excluding samples with an average holding period greater than investment experience). Furthermore, considering potential biases in the actual participation in the survey, the questionnaire underwent appropriate weighting adjustments based on investor account structure data published in the Shanghai Stock Exchange Statistical Yearbook, aiming to align the sample distribution as closely as possible with the overall distribution of Chinese investors. It is worth noting that there were no significant differences in the distribution of stock investor demographic characteristics in the questionnaire before and after adjustments, indicating the reliability of the survey data. Additionally, the questionnaire survey only involved active investors and did not include inactive investors (inactive investors referring to individuals who, after opening a stock account, either did not engage in actual stock trading, traded infrequently, or had participated in stock trading but subsequently did not close their accounts).

Table 1. Definition of variables

Variable	Definition
RET	Retail investors invest for themselves or for their family members.
INS	Institutional investors invest for other investors and companies.
ET	Excessive trading refers to a holding period less than 3 months.
BB = OVER	Overconfidence bias.
BB = RISK	Risk-seeking bias.
BB = DISP	Disposition effect bias.
BB = SENS	Sensation-seeking bias.
RP	Risk perception is measured by the forecast of when the COVID-19 pandemic will end, ranging from grade 1 (within three months), grade 2 (within six months), grade 3 (within a year), to grade 4 (over a year).
AGE	Age.
MAL	Gender = male.
MAR	Marital status = married.
EDU	Education (years).
EXP	Investment experience (years).
INV	Investment amount, ranging from grade 1 (<=10K) to grade 12 (>30M).
RUL	Investors strictly follow the rules of take profit and stop loss.
FUN	Investors make decisions based on fundamental analysis.
LEV	Investors use leverage instruments.
BUL	Investors expect the stock market to be bullish.

This study aims to explore the trading behavior of different stock investors, thus categorizing respondents in the questionnaire into retail investors (RET, representing individuals, families, or friends engaging in stock investment) and institutional investors (INS, representing industrial enterprises or financial and investment institutions engaged in stock investment). The minimum age for this study is set at 18 years old, and investors aged 75 and above were excluded from the analysis. The variables of the survey data are defined in Table 1. The first two variables are types of investors (RET and INS). The following set of variables is the three key variables (ET, BB, RP). The control variables can be classified as demographic controls (AGE, MAL, MAR, EDU) and investment controls (EXP, INV, RUL, FUN, LEV, EXP).

The descriptive statistics of these variables are reported in Table 2. It is shown that institutional investors are more likely to engage in ET than retail investors (0.810>0.626). It seems to be mainly attributed to a higher level of BB in the form of overconfidence (0.523>0.367), which coincides with a more optimistic RP (tend to believe the pandemic will end sooner 2.240<2.488). Specifically, note that we proxy the level of RP by people's forecast of when the COVID-19 pandemic will end. If they believe it will end sooner, then they have a lower level of RP; if they believe it will end later, then they have a higher level of RP.

Specifically, we use the question "How long do you expect the COVID-19 pandemic to end?" as a measure of risk perception. We have the following justifications for this measure. First, the question directly addresses the temporal aspect of the pandemic, reflecting individual's uncertainty about when it will end. The perceived duration of the pandemic can influence decisions related to investments, travel, employment, and other aspects of life. A longer-anticipated duration may also lead to increased stress and anxiety, influencing risk aversion and decision-making. Second, business and economic decisions often rely on expectations of future conditions. If individuals expect a prolonged pandemic, they may adjust their financial strategies, spending habits, and investment decisions accordingly. In financial markets, investor sentiment plays a crucial role. The perceived duration of the pandemic can impact market sentiment, affecting stock prices and investment strategies. Third, governments and public health organizations use public perceptions of the pandemic's duration to inform communication strategies, policy development, and resource allocation. Risk perception is closely linked to compliance with public health measures. Understanding how long people expect the pandemic to last can provide insights into their willingness to adhere to guidelines and recommendations from health authorities.

Table 2. Descriptive statistics

	Full Sample		*RETA Subsample*		*INST Subsample*	
	Obs.	Mean (Std. Err.)	Obs.	Mean (Std. Err.)	Obs.	Mean (Std. Err.)
ET	31,456	0.658 (0.474)	23,049	0.626 (0.484)	5,701	0.810 (0.392)
BB = OVER	31,456	0.415 (0.493)	23,049	0.367 (0.482)	5,701	0.523 (0.500)
BB = RISK	31,456	0.532 (0.499)	23,049	0.568 (0.495)	5,701	0.504 (0.500)
BB = DISP	31,456	0.699 (0.459)	23,049	0.718 (0.450)	5,701	0.658 (0.474)
BB = SENS	31,456	0.785 (0.411)	23,049	0.790 (0.407)	5,701	0.794 (0.404)
RP	11,513	2.433 (1.115)	8,105	2.488 (1.185)	2,695	2.240 (0.882)
AGE	31,456	41.14 (12.21)	23,049	41.04 (11.86)	5,701	40.93 (13.01)
MAL	31,456	0.556 (0.497)	23,049	0.553 (0.456)	5,701	0.581 (0.419)
MAR	31,456	0.711 (0.453)	23,049	0.730 (0.500)	5,701	0.663 (0.489)
EDU	31,456	15.26 (2.258)	23,049	15.33 (11.85)	5,701	14.94 (13.01)
EXP	31,456	6.863 (5.712)	23,049	7.174 (0.497)	5,701	5.657 (0.494)
INV	31,456	4.37 (2.017)	23,049	4.200 (0.444)	5,701	4.590 (0.473)
RUL	31,456	0.654 (0.476)	23,049	0.626 (2.225)	5,701	0.796 (2.312)
FUN	31,456	0.655 (0.475)	23,049	0.727 (5.778)	5,701	0.480 (4.873)
LEV	31,456	0.279 (0.449)	23,049	0.247 (1.974)	5,701	0.434 (1.720)
BUL	31,456	0.782 (0.413)	23,049	0.794 (0.484)	5,701	0.841 (0.403)

This paper focuses on the determination of ET, so we elaborate on its variations in terms of spatial heterogeneity and temporal variation. As shown in Figure 2, provinces with low development (e.g., Yunnan, Qinghai, Tibet, Xinjiang) have low levels of ET. In the meantime, provinces with high development (e.g., Guangdong, Jiangsu, Beijing, Shanghai) also have low levels of ET. Provinces with intermediate development (e.g., Sichuan, Jiangxi, Fujian, Inner Mongolia) have high levels of ET. Therefore, the relationship between development and ET seems to be nonlinear. Regardless of the pattern, spatial heterogeneity requires our model to include province fixed effects.

The level of ET also changes over time. In 2021, the COVID-19 pandemic was in full force. Most people perceived that it would not end soon, so there had been a high level of RP. By contrast, the World Health Organization had declared an end to the public health emergency of international concern of the COVID-19 pandemic in May 2023, so people had a lower level of RP during the second wave of the survey. As shown in Figure 3, the level of ET has increased in almost all provinces except for Tibet as people became more optimistic (lower level of RP). It seems to suggest a negative link between RP and ET. Again, the systematic difference between the two waves requires our model to have time or wave fixed effects.

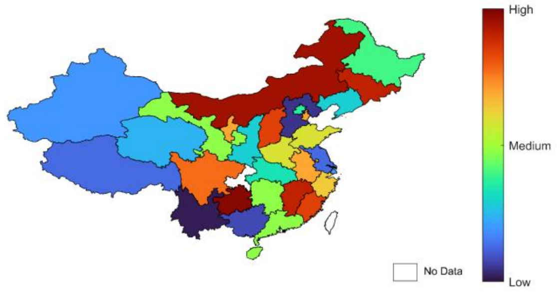

Fig 2. Spatial Heterogeneity of Excessive Trading

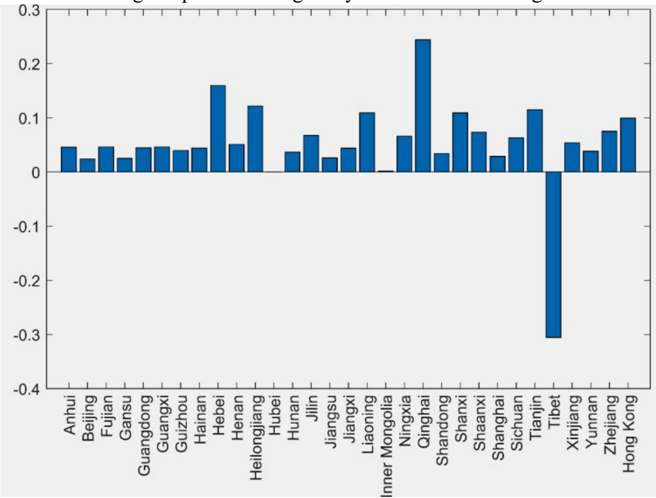

Fig 3. Temporal Variation of Excessive Trading

3.2.Model

To explain ET, we propose a structural equation model (SEM) which reflects the conceptual framework Figure 1. In contrast to simple-equation linear regressions, one critical advantage of SEM is that it is capable of capturing endogeneity of the key variable BB. Our literature review has provided solid evidence that BB is not random but rather related to investor's demographic features and risk preferences. Without considering the endogeneity of BB, the OLS estimate of the effect of BB on ET is subject to self-selection bias. A popular alternative method of addressing endogeneity or self-selection bias is 2SLS, but it is very difficult to find valid and strong instrumental variables. 2SLS is a limited-information estimator, which is inferior to the full-information estimator (e.g., SEM) in terms of efficiency.

The SEM has two equations, a selection equation describing how BB is determined, and an outcome equation describing how ET is determined. The selection equation (1) for BB_i follows a probit specification, with the key determinant RP_i and control variables z_i as well as province fixed effects FE_p and wave fixed effects FE_t (time fixed effects).

$$\Pr(BB_i=1) = \Phi\left(\alpha\times RP_i + z_i'\alpha + FE_p + FE_t\right) \qquad (1)$$

where $\Phi(\cdot)$ is normal CDF.

To correct the self-selection bias of BB, we apply the two-part method originally developed by Lee (1978). It is similar to but more general than the Heckman selection model. The essence is to estimate the Inverse Mill's Ratio (IMR) for both BB_i=0 and 1 based on (1).

$$IMR_i = \left(\frac{\phi(\hat{s}_i)}{\Phi(\hat{s}_i)}\right)^{BB_i}\left(\frac{-\phi(\hat{s}_i)}{1-\Phi(\hat{s}_i)}\right)^{1-BB_i} \qquad (2)$$

where $\hat{s}_i = \hat{\alpha}\times RP_i + z_i'\hat{\alpha} + \widehat{FE}_p + \widehat{FE}_v$

The outcome equation (3) for ET_i is a linear regression, where we include the IMR_i calculated above as well as BB_i and the interactive term $BB_i\times RP_i$ in addition to the controls:

$$ET_i = IMR_i + \beta\times BB_i + \gamma\times BB_i\times RP_i + z_i'\beta + FE_p + FE_t + \epsilon_i. \qquad (3)$$

In general, we define BB_i=1 if any of the four types of BB_i (overconfidence $OVER_i$, risk-seeking $RISK_i$, disposition effect $DISP_i$, and sensation-seeking $SENS_i$) is equal to 1. As a result, equation (1) can have four variants if we replace BB_i by $OVER_i$, $RISK_i$, $DISP_i$, and $SENS_i$. Similarly, equation (3) can also have four corresponding variants. The baseline model can be used to test hypotheses [H1] $\alpha\neq 0$, [H2] $\beta\neq 0$, and [H3] $\gamma\neq 0$, while these variant models can be used to test hypotheses [H1abcd], [H2abcd], and [H3abcd].

4.Results

The SEM is estimated as a system. BB is both a dependent variable in the selection equation and an independent variable in the outcome equation. Another link between the two equations is that IMR computed based on the estimated selection equation is included when estimating the outcome equation to correct for self-selection bias. Estimation results of the selection equation can be used to test hypotheses [H1] and its variants, and those of the outcome equation can be used to test hypotheses [H2]-[H3] and their variants.

4.1.Selection Equation

We first report the estimation results for selection equation (1) and its four variants in Table 3, where three key findings can be drawn. First, risk perception does not contribute to the overall measure of behavioral bias (BB), so [H1] is rejected. As shown in column (1) of Table 3, RP has an insignificant coefficient in explaining the overall measure of BB. It can be either that RP is not related to BB or that the effects of RP on BB are mixed for different types. To distinguish between the two possibilities, we refine the measure of BB into the four types so we can separately test the sub hypotheses [H1a]-[H1d]. The following two findings are based on the refined measures of BB. Second, risk perception has significant effects on overconfidence [H1a] and risk-seeking [H1d]. Columns (2) and (3) imply that a higher level of RP leads to higher levels of overconfidence (0.173***) and risk-seeking (0.144***). Third, risk perception does not affect disposition effect [H1b] and sensation-seeking [H1c]. In columns (4) and (5), the coefficients of RP are insignificant. Therefore, these two types of BB contribute to insignificant results in the overall measure. These findings make sense as risk perception is cognitive foundation for behavioral biases related to risk (overconfidence and risk-seeking), but less relevant to behavioral biases related to loss aversion (disposition effect) and novelty attention (sensation-seeking).

In addition, the control variables in Table 3 also return some interesting patterns. For demographic controls, a higher age can reduce the tendency of behavioral bias, but overconfidence is an exception. Male investors are more risk-seeking, but less subject to disposition effect. Marriage (MAR) can increase overconfidence, disposition bias, and sensation-seeking, while education (EDU) can increase risk-seeking. For investment controls, longer experience (EXP) raises the likelihood of risk-seeking, total investment (INV) reduces it. Rule-followers (RUL) and fundamental analysts (FUN) have opposite influences on behavioral biases. Overall, it seems that rule-based investment can reduce the tendency of behavioral biases, while fundamental analysis exacerbates biases. Leverage users (LEV) usually have stronger risk preferences, so they have higher levels of overconfidence and risk-seeking biases, in line with the effects of RP. Optimistic expectations (BUL) suppress overconfidence and disposition effect while raising risk-seeking, leaving the overall effect on BB insignificant.

Table 3. The Selection Equation (RP → BB)

	(1)	(2)	(3)	(4)	(5)
	BB	*OVER*	*RISK*	*DISP*	*SENS*
RP	-0.00374	0.173***	0.144***	-0.040	0.012
	(0.0466)	(0.0248)	(0.0232)	(0.0240)	(0.0259)
AGE	-0.00666***	-0.00102	-0.00452***	-0.00476***	-0.00464***
	(0.00200)	(0.00113)	(0.00108)	(0.00109)	(0.00117)
MAL	0.0728	-0.00710	0.171***	-0.0793***	-0.000135
	(0.0457)	(0.0246)	(0.0228)	(0.0237)	(0.0255)
MAR	0.109**	0.0919***	-0.0283	0.129***	0.136***
	(0.0517)	(0.0280)	(0.0264)	(0.0270)	(0.0289)
EDU	-0.0138	-0.00226	0.0215***	0.00371	0.00108
	(0.0108)	(0.00568)	(0.00537)	(0.00550)	(0.00590)
EXP	0.00539	-0.00287	0.0132***	0.000734	0.00151
	(0.00460)	(0.00233)	(0.00235)	(0.00239)	(0.00256)
INV	-0.0268**	0.00782	-0.0469***	-0.0130**	0.0402***
	(0.0119)	(0.00654)	(0.00622)	(0.00632)	(0.00686)
RUL	-0.0897*	0.203***	0.0559**	-0.187***	-0.00843
	(0.0533)	(0.0294)	(0.0265)	(0.0278)	(0.0297)
FUN	0.372***	-0.0862***	0.274***	0.200***	0.137***
	(0.0470)	(0.0261)	(0.0245)	(0.0252)	(0.0270)
LEV	0.157***	0.236***	0.208***	-0.0204	0.0355
	(0.0514)	(0.0255)	(0.0246)	(0.0252)	(0.0274)
BUL	0.0321	-0.138***	0.374***	-0.0664**	0.0299
	(0.0580)	(0.0329)	(0.0297)	(0.0313)	(0.0332)
Province FE	YES	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES	YES
Observations	13,067	11,360	13,186	13,183	13,183

Notes: Standard errors in parentheses. Significance: *** 0.01 ** 0.05 * 0.1.

4.2.Outcome Equation

Based on the IMR computed in the selection equation, we can then estimate the outcome equation (2) in Table 4. Despite insignificant in the overall measure of BB, the IMR term plays a critical role in correcting selection bias in explaining overconfidence in column (2), risk-seeking in column (3), and disposition effect in column (4). This provides supporting evidence for using SEM over OLS.

Starting with the key regressors, the general measure of BB does not contribute to ET ([H2] rejected), but it has a significant moderation effect ([H3] accepted). In other words, RP has a moderation effect on ET via BB, but it does not have a mediation effect via BB. Nevertheless, if we separate the overall measure of BB into the four refined types, overconfidence ([H2a]), risk-seeking ([H2b]), and disposition effect ([H2c]), most coefficients become significant. Sensation-seeking is the only insignificant case ([H2d]).

The insignificant result in column (1) is because overconfidence and risk-seeking tend to encourage over-trading, while disposition effect and sensation-seeking tend to encourage under-trading. Their opposite effects cancel out each other in the overall measure of BB. Therefore, the mediation effect of BB on the RP-ET relationship is present but mixed. In contrast, the moderation effect of RP on the BB-ET relationship is positive and significant for all cases—a higher RP can exacerbate the effect of BB on ET.

Like the selection equation, we control both demographic characteristics and investment characteristics in the outcome equation. It is found that a higher tendency of ET is associated with younger, male, single, and more educated investors. More experienced investors with higher stakes are less likely to engage in ET. We again find that rule-based and fundamental-based investment strategies lead to opposite directions in ET. Rule followers have higher levels of ET while fundamental analysts have lower levels of ET. Finally, leverage users and bull market believers are more active in overtrading.

We have tested the robustness of the results in Table 3 and Table 4 by a different measure of RP (expecting the pandemic to end within 3 months rather than 6 months), a different estimation method (limited-information estimator rather than full-information estimator), and a different specification (fractional regression rather than linear regression for the outcome equation). All conclusions we obtained in this section stay qualitatively the same.

As a handy tool, we use the path diagram (Figure 4) to summarize the findings of the SEM and hypotheses. It conveniently and intuitively presents the results of hypothesis tests based on the estimated model (1)-(2) and its variants. For the baseline model using the overall measure of BB, it is shown that RP only serves as a moderation effect, not a mediation effect. In contrast, for specific measures of BB, RP can also have mediation effects via overconfidence and risk-seeking biases.

Table 4. The Outcome Equation (BB → ET)

	(1)	(2)	(3)	(4)	(5)
	ET	*ET*	*ET*	*ET*	*ET*
IMR	0.363	-1.286***	-1.653***	3.550***	0.288
	(0.333)	(0.307)	(0.341)	(0.548)	(0.455)
BB	-0.885				
	(0.762)				
BB×RP	0.237***				
	(0.0250)				
OVER		2.070***			
		(0.515)			
OVER×RP		0.104*			
		(0.0533)			
RISK			2.732***		
			(0.567)		
RISK×RP			0.122***		
			(0.0428)		
DISP				-5.936***	
				(0.909)	
DISP×RP				0.138***	
				(0.0303)	
SENS					-0.573
					(0.799)
SENS×RP					0.215***
					(0.0275)
AGE	-0.00347***	-0.000659	0.00189	-0.0129***	-0.00355**
	(0.00124)	(0.00126)	(0.00152)	(0.00194)	(0.00162)
MAL	0.122***	0.110***	-0.0636	-0.0383	0.118***
	(0.0247)	(0.0265)	(0.0429)	(0.0343)	(0.0242)
MAR	-0.0296	-0.112***	-0.00795	0.226***	-0.0191
	(0.0292)	(0.0350)	(0.0292)	(0.0499)	(0.0422)
EDU	-0.0240***	-0.0231***	-0.0458***	-0.0158***	-0.0239***
	(0.00594)	(0.00635)	(0.00729)	(0.00599)	(0.00584)
EXP	-0.0195***	-0.0165***	-0.0334***	-0.0181***	-0.0196***
	(0.00246)	(0.00255)	(0.00365)	(0.00245)	(0.00246)
INV	-0.0544***	-0.0609***	-0.00415	-0.0796***	-0.0481***
	(0.00675)	(0.00716)	(0.0118)	(0.00758)	(0.0112)
RUL	0.540***	0.461***	0.489***	0.186***	0.547***
	(0.0272)	(0.0489)	(0.0293)	(0.0624)	(0.0268)
FUN	-0.0653*	-0.0374	-0.378***	0.317***	-0.0676*
	(0.0338)	(0.0336)	(0.0636)	(0.0685)	(0.0409)
LEV	0.186***	-0.0199	-0.0386	0.139***	0.185***
	(0.0277)	(0.0540)	(0.0508)	(0.0273)	(0.0275)
BUL	0.217***	0.349***	-0.185**	0.0795**	0.216***
	(0.0307)	(0.0422)	(0.0856)	(0.0369)	(0.0313)
Province FE	YES	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES	YES
Observations	13,063	11,356	13,182	13,179	13,179

Notes: Standard errors in parentheses. Significance: *** 0.01 ** 0.05 * 0.1.

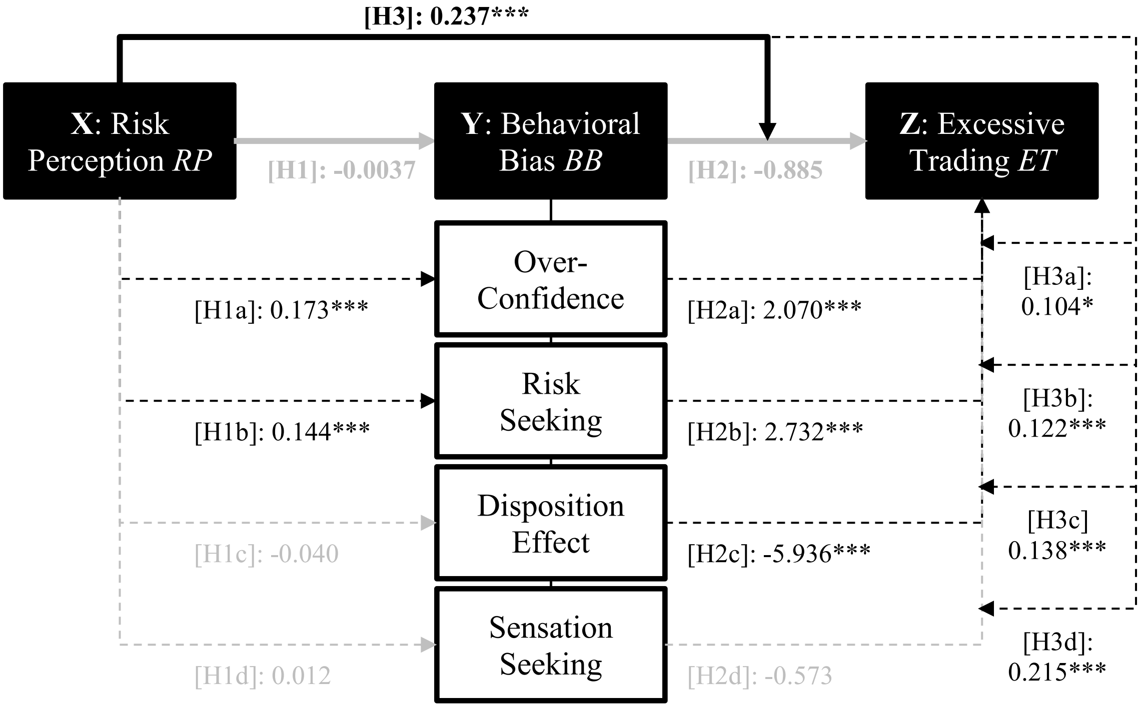

Fig 4. The Path Diagram

5.Heterogeneities

As shown in Figure 2 and Figure 3, there are substantial spatial and temporal variations in ET. To further investigate the heterogeneities in the RP-BB-ET relationship, we perform two sets of subsample estimations. We first divide the full sample into three regions of China (east, middle, and west) to reflect spatial heterogeneity, and then divide the full sample into two waves of the survey (first half and second half of the pandemic) to reflect the temporal variation.

5.1.Spatial Heterogeneity

Economic development in China is geographically unbalanced, with the eastern region most developed and the western region least developed. The imbalance is also embodied in investors' local culture and the RP-BB-ET relationship[13,14]. Table 5 presents the estimation results for the three regional subsamples.

Table 5. Spatial Heterogeneity

	Selection Equation			Outcome Equation		
Dep. Var.	BB	BB	BB	ET	ET	ET
Region	West	Middle	East	West	Middle	East
RP	0.237*	-0.0091	-0.0553			
	(0.127)	(0.0849)	(0.0623)			
BB				-3.461**	-1.360	-0.766
				(1.742)	(1.294)	(0.875)
BB×RP				0.192***	0.262***	0.245***
				(0.0651)	(0.0494)	(0.0323)
Controls	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES
Observations	2,082	3,395	7,680	1,963	3,395	7,680

Notes: Standard errors in parentheses. Significance: *** 0.01 ** 0.05 * 0.1.

In the selection equation, the effect of RP on BB is positive for the western region, while insignificantly negative for the middle and eastern regions. One explanation for this regional heterogeneity is that behavioral biases are more likely to appear in less developed economies due to lower education and investment experience[15], so BB is more sensitive to various factors like RP.

Turning to the outcome equation, the effect of BB on ET is again only significant for the western region. It suggests that the excessive trading behavior of investors in the west are more sensitive to various behavioral biases. The overall sign of BB on ET is negative, implying that the negative disposition effect dominates the positive effects of overconfidence and risk-seeking (see Figure 4). On the other hand, the moderation effects are significant for all regions, in line with the result of full sample, but the western region stands out with the weakest moderation effect. Thus, there seems to be a trade-off between the mediation effect and moderation effect as in other empirical research[47].

5.2.Temporal Variation

Investors in different macroeconomic conditions tend to have different risk perceptions and behavioral biases[13]. The data were collected in two waves, one in the middle of the COVID-19 pandemic and the other in the end of the pandemic. Sentiment can change substantially regarding market uncertainties. To capture temporal variation, we report the estimation results for the two waves separately in Table 6.

Consistent to the baseline results in Table 3, RP does not have significant impacts on the overall measure of BB in both years. However, the effects are significant for OVER in 2021 and for both OVER and RISK in 2022. It suggests that, as the pandemic approaches the end, the ratio of excessive trading is more sensitive to risk-related behavioral biases, but the effects of RP on DISP and SENS are still insignificant like those in the baseline result.

In the outcome equation, the mediation effect is weak if an overall measure is used, but the moderation effect is significant in both years. When the four types of BB are separately used, the mediation effect also becomes significant, especially for the later wave. Stronger effects in 2022 reflect the recovery of dynamism in the financial market.

Table 6. Temporal Variation

	Selection Equation		Outcome Equation	
Dep. Var.	BB	BB	ET	ET
Wave	2021	2022	2021	2022
RP → BB	-0.0742	0.0397		
	(0.0998)	(0.0534)		
RP → OVER	0.533***	0.151***		
	(0.105)	(0.0256)		
RP → RISK	-0.0319	0.183***		
	(0.0532)	(0.0260)		
RP → DISP	-0.0157	-0.0268		
	(0.0564)	(0.0269)		
RP → SENS	-0.0198	0.0254		
	(0.0623)	(0.0287)		
BB → ET			-1.384	-1.329
			(1.667)	(0.890)
BB×RP → ET			0.256***	0.220***
			(0.0546)	(0.0285)
OVER → ET			1.581	2.655***
			(1.990)	(0.594)
OVER×RP → ET			0.0468	0.0762
			(0.249)	(0.0570)
RISK → ET			2.963**	2.515***
			(1.232)	(0.648)
RISK×RP → ET			0.152	0.107**
			(0.0938)	(0.0492)
DISP → ET			-3.011	-5.458***
			(1.871)	(1.118)
DISP×RP → ET			0.176***	0.136***
			(0.0649)	(0.0354)
SENS → ET			2.946	-0.242
			(1.900)	(1.021)
SENS×RP → ET			0.223***	0.197***
			(0.0585)	(0.0317)
Controls	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Constant	YES	YES	YES	YES

Notes: Standard errors in parentheses. Significance: *** 0.01 ** 0.05 * 0.1.

6.Conclusion

Since 1990s, financial markets in China have experienced significant growth, accompanied by an increase in individual participation in trading activities. Recently, the COVID-19 pandemic resulted in multiple waves of fluctuations of market sentiments and asset prices, generating big challenges to financial stability. Hence, up-to-date, evidence-based understanding of investor behavior is paramount for researchers, investors, and policymakers.

Building on literature on behavioral finance, we establish a structural equation model of risk perception, behavioral bias, and excessive trading. The model can deal with the endogeneity issue when estimating the complicated relationships among the three variables. Based on a two-wave, investor-level survey in China, we find that risk perception has a significant moderation effect, but the mediation effect only exists for two specific types of behavioral bias (overconfidence bias and risk-seeking bias). In addition, we document spatial heterogeneity (particularly in the western region) and temporal variation (particularly in the later stage) of the results. The timely research, utilizing survey evidence at the investor level, offers valuable firsthand insights for comprehending the microstructure of the financial market in China. This is particularly crucial for policymakers striving to attain financial stability. We draw the following policy implications based on the evidence we find in this paper.

First, confirmed moderation effects and mediation effects suggest that policy interventions addressing relevant biases may yield more direct and impactful results in promoting financial stability. More fundamentally, policymakers should tailor strategies to enhance risk awareness and perception, particularly targeting overconfidence and risk-seeking tendencies, to foster more informed and rational decision-making among investors and ultimately contribute to a more stable financial environment.

Second, given that the western provinces exhibit a stronger mediation effect but a weaker moderation effect, policymakers should recognize the diverse dynamics at play in various regions and tailor interventions accordingly. Strategies aimed at addressing mediation effects, particularly in the western provinces, may require targeted measures to mitigate specific risk factors. Simultaneously, efforts to enhance moderation effects might necessitate nuanced approaches that account for the unique characteristics of each region. This region-specific understanding is crucial for formulating effective financial stability policies that accommodate the distinct challenges and opportunities present in different areas.

Third, stronger effects in the later stage of the pandemic indicate a shifting landscape in investor behavior and risk dynamics. Financial stability policies should be adaptive and responsive to the evolving conditions. Given the increased influence of RP in both mediating and moderating effects, policymakers may consider interventions that specifically target risk perception at different stages of the pandemic recovery. Strategies aimed at enhancing investors' understanding of risks and bolstering risk management practices could be particularly effective. Furthermore, policymakers may need to monitor and adjust policies dynamically as the environment evolves, ensuring that regulatory frameworks and support mechanisms align with the changing patterns of mediation and moderation effects. This adaptive approach is essential for promoting financial stability in the face of the dynamic and evolving nature of investors' trading behavior.

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