RESEARCH ARTICLE

Research on the impact of investor sentiment on the yield of the real estate sector

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ABSTRACT

This study investigates the interaction between investor sentiment and macroeconomic environment in China's real estate sector from 2013 to 2023. Using a dataset combining psychological measurements from 2,156 investors with market data from 148 listed real estate companies, we examine how monetary policy and market structure shape the transmission of emotional effects. Through empirical analysis integrating emotional psychology and behavioral finance theories, we identify three key mechanisms: (1) monetary policy environment significantly moderates emotional transmission in the market, with loose policy periods amplifying sentiment effects; (2) market structure and investor composition determine the strength of emotional contagion, showing stronger effects in retail-dominated markets; (3) social networks and institutional arrangements systematically influence how individual emotions aggregate into market-wide sentiment. Our results demonstrate that the impact of investor emotions varies substantially with macroeconomic conditions and market structure, revealing the crucial role of policy environment and institutional framework in emotional transmission. These findings provide insights for maintaining market stability through coordinated management of monetary policy, market structure, and collective sentiment.

Keywords: investor sentiment; real estate sector; monetary policy; market structure; emotional contagion; institutional environment

1. Introduction

The mindset of investors is regarded as one of the most powerful influences on financial markets, particularly in sensitive areas such as real estate [1]. In the subsequent years, many scholars have focused on the combination of monetary policies and structured markets along with the emotional sentiments of investors triggered in the primary market which systematically creates market outcomes resulting in deviation from rational behaviour at both individual and group levels[2,3]. Knowledge of how these systems interact has become critical at a time when the global real estate markets are dealing with heightened volatility due to macroeconomic factors[4].Real estate markets are one of the most important sectors in the worldwide economy as the estimated value of real estate reached USD 379.7 trillion in 2022, exceeding the total value of equities and debt securities combined, and equating to almost four times the GDP of the world[5]. Furthermore, in China, the real estate industry accounts for approximately 25%-30% of the

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country's GDP when examining the direct and indirect contributions, underscoring the importance of the sector to the economy[6]. This colossal economic footprint increases the already heightened psychological effect of the changes in the real estate market on the behaviour of investors, establishing distinct circulatory systems between investor sentiment and macroeconomic effects.

Behavioral frameworks argue that extremes of emotional impact on market outcomes depend on the institutional and policy frameworks in place[7,8]. On the other hand, traditional finance is heavily focused on real estate and corporation-level phenomena. Real estate as an asset is also psychologically fascinating because of spatial fixity, physical heterogeneity, and attachment value.Unlike financial assets, real estate properties are tangible, and empirical research indicates that this characteristic heightens sentiments towards loss aversion compared to equity investors. Other manifestations of heightened emotional response that have been documented include status quo visualisations and reduced geographical diversity prompted by increased familiarity. Property owners systematically overvalue their holdings as a result of the endowment effect. Moreover, real estate markets tend to show momentum patterns that are not consistent with the efficient market hypothesis, while price cycles usually lag behind essential economic indicators.

A notable methodological dilemma in behavioural finance concerns the gap between self-reported emotional states and behaviour in investments. The implementation of sentiment analysis and emotional quotient tests from the psychometric inventory is useful; however, several biases in judgement may interfere with real-time activities in the marketplace. Barber and Odean's research shows that investors have a gap between the stated preferences in the surveys and the actual trading behaviour, including most investors trading more often than is reasonable according to the stated investment strategy[10]. Hoffmann, Post, and Pennings also found that while self-reported perceptions of risk and return change substantially during crises, those shifts do not always result in proportional changes in trading activity[11]. These findings stress the merit of complementing survey data with actual behavioural data drawn from the marketplace to strengthen the rigor of behavioural finance research.

Real estate represents a unique setting where an interaction between investor psychology and market structure, aside from being affected by policies and institutional frameworks, operates in a rather strong manner at deepening emotional contagion[12]. During certain market phases, this emotional contagion appears to be particularly muted. In this case, investors' psychology can exacerbate extreme price movements (in both directions) to levels which fundamentally are quite distant from what would be reasonable given the basic value drivers. For example, in financial crises, the pessimistic flocking behaviour of stock investors leads to deeply depressed returns in real estate pari passu illustrating the dictatorship in value-pricing frameworks due to uncertainty [11].Real estate's unique features, such as high transaction costs as well as an inherent asymmetry in the information available to different parties involved in the transaction, make the real estate market especially vulnerable to psychological pitfalls due to its lack of liquidity. Such market inefficiencies stemming from behavioural mechanisms affect a market's effectiveness to exploit arbitrage opportunities, if they exist. At the same time, market participants are often subject to extreme psychological burdens owing to the large value involved in real estate transactions, such as a residential house which could, at very least, represent a large part of an investor's portfolio, influencing rational judgement solidifying under biases of overconfidence, anchoring and bias leaning towards the most recent event.

Even with the increased sensitivity concerning psychological issues in financial markets, the impact of macroeconomic considerations and institutional contexts on their emotions remains largely unexplored[13]. There is a notable lack of understanding concerning the ways in which the systems of monetary policy and the microstructure of the market simultaneously influence the psychology of the investors in the real estate market. Prior research has approached this issue as a static system; however, evidence indicates that there is a dynamic relationship dependent on the particular policy regime and prevailing market structure.

This study examines how monetary policies, market structures, and emotional dynamics interact in the real estate market, while placing particular emphasis on the processes through which institutions influence collective emotions and the resulting market behaviours. The framework integrates monetary policy economics and behavioural finance, offering a valuable perspective on how politics and market systems contribute to emotional flows[14]. Tracking the dissemination of emotions extends beyond sentiment analysis, and in this regard, our framework highlights policy impacts and institutional arrangements within social networks and market systems[15]. This aids in understanding how pervasive macroeconomic realities, estimable alongside market structures, affect collective sentiment in capital markets.To address this gap, our research records changes in investor sentiment towards real estate returns within different policy contexts and structural market frameworks as a form of sentient regimes. Combining psychological survey data with market data aids in bridging the divide between individual psychology and market phenomena, advancing the discourse in behavioural finance and providing actionable insights for practitioners and policymakers.

2. Theoretical framework and literature review

2.1. Psychological foundations of investor emotion and market environment

The relation between investor sentiment and financial markets resides in a complex adaptive system where psychological factors are intricately connected to macroeconomic variables through dynamic feedback loops[16]. Recent developments in behavioural economics demonstrate how systematically boundary-shaping monetary policy combined with market architecture affects emotions regarding collective risk appraisal and value determinations as follows[17]. Instead of an overly simplistic investor irrationality assumption, institutional strategies for understanding market behaviour offer an explanation on how emotionally responsive policy environments, within predetermined structures, harness and transform emotions at the individual and group level[18].

Such an environment-emotion interaction system is prominent in the policies impacting sectors such as real estate, which is governed by an institutional framework that heavily regulates the application of real estate, which is biased in terms of psychology[19]. Barberis and Thaler[8] showed the limits of models based on rational expectations, but did not investigate the impact of different institutional contexts on the biases emanating from these frameworks. Similarly, Baker and Wurgler[3] demonstrated the impact of sentiment on cross-sectional returns but did so in a framework that does not control for how monetary policy regimes suppress these impacts—this study's main answerable gap.

Monetary policy affects market sentiment through three main transmission mechanisms: liquidity constraints which determine the risk appetite, policy indications which shape approach sentiment, and the anchor expectation which adjusts the psychological benchmark region[20]. In addition to these 'first-round' effects, the reconfiguration of policy structures changes the sentiment information infrastructure system as it alters information cascade structures, herding thresholds, and social contagion dynamics[21]. In real estate markets specifically, Chen et al.[22] documented how changes in policy-induced collateral values affect investment decisions, but the psychological factors that drive this relationship were ignored—this is yet another gap that our study attempts to fill.

There is a wealth of research explaining the behavioural outcomes of policy conditions imposed on the market, yet the gap and lack of discussion remain around the understanding of the psychological policy framework required to form collective sentiment. Clayton[17] formulated some of the capital flows and asset valuations interactions. However, the absence of integrated psychological data to validate these constructs is evident. This gap is precisely what we sought to address by combining psychological evaluations with market data in a manner that examines how systematic alteration of policies allows individual emotions to be cast into collective market sentiment.

2.2. Social dynamics of market sentiment

Sentiment as a whole is transmitted via intricate social-psychological pathways that exceed the scope of individual understanding. Group Polarization Theory describes how homogenous investment societies amplify shared emotions and judgment inclinations which results in self-reinforcing sentiment cycles increasingly divorced from fundamental valuations, as noted in reference[23]. This explanation helps illuminate why excessive optimism or pessimism in real estate markets tends to develop momentum which outlasts rational economic models' predictions.

Social Identity Theory adds an important, yet insufficiently analysed, angle to the problem of collective investment behaviour. When people strongly categorise themselves with different investment types ("value investor," "real estate investor"), these social categories have strong emotive and prescriptive power on conduct and decision making, reference[22]. Malmendier and Tate[24] analysed the consequences of overconfident CEOs on corporate investments, but did not investigate how social identity might weaken these arguments—whereas this study aims to fill the gap regarding how identification with an investor group activates emotional contagion cycles.

Prior literature does not sufficiently address how social comparison phenomena serve to heighten emotions in the context of investing in real estate. Brown and Cliff[12] noted the sentiment effects concerning asset valuation but did not focus on the social comparison processes that accentuate those effects. This is the void that our research attempts to address by studying the extent to which balanced benchmarks make real estate emotional states and risk-taking behaviours more extreme[25], especially in the context of markets where asset value information is readily available and easily observable.

An important gap in the research extends to the assumption that all constituents within an investor group function as a single unit. Chakravarty[14] provided evidence showing the differential price impact of various trader types but failed to explain these divergences through the lens of underlying psychology. This is the gap we aim to fill by focusing on the impact of investor group heterogeneity—in particular emotional intelligence, social capital, and vertical institutional framework—to the intensity of emotional contagion processes.

2.3. Emotional biases in real estate investment

Due to the specific psychology of property assets, real estate investment decisions incur the most critical impact from emotional biases[24]. Unlike other asset classes, real estate markets tend to exhibit greater effects of loss aversion due to the psychological ownership and emotional attachment investors feel towards physical properties[26]. The endowment effect is even more pronounced, as property owners tend to unfairly value their properties higher than the price at which they would sell them compared to market valuations[27]. This creates a major disconnect in the frameworks of traditional finance models which rely on the inter-temporality of asset classes.

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Emotions that investors face in times of uncertainty are best explained with Prospect Theory and how it biases investment decisions makes Los Angeles and the Surrounding Areas practically irrational from the point the South Bay utilises this framework[28]. To the best of my knowledge, Weinstein[25] demonstrates unrealistic optimism without exploring how this optimism comes through macroeconomic conditions and therefore becomes a gap in research for our study addressing emotional biases across different monetary policy environments.

A significant gap in the previous research focuses on the intersection of psychological factors and liquidity conditions of the market. The combination of the illiquid nature of the real estate market, alongside the liquidity premium attached to property transactions, suggests that emotional biases are likely to be exacerbated more compared to other liquid markets[29]. However, previous studies have overlooked these biases as being adaptive to changing market dynamics. This research seeks to fill the gap by analysing how emotional impacts are inflicted differently depending on the prevailing market structures and liquidity levels in various markets.

Literature overlooking the impact of macroeconomic sentiment as a regulating factor on the emotional aspects in the real estate market is well documented. For example, in the course of economic expansions, the psychology of loss aversion tends to relax due to easy credit availability and increasing asset prices serving as cognitive buffers. This increasingly risky segment, however, is countered during contractions dominantly amplifying the perception of risk exaggerates loss aversion. Understanding the intertwining mechanisms of macroeconomics and psychology, in the context of real estate market dynamics and the gap our study addresses.

2.4. Research hypotheses

Given the theoretical approaches discussed earlier, along with the existing gaps in literature, we formulate five psychologically advanced hypotheses concerning the mechanisms underlying behaviour in real estate investment.

H1: Real estate investment decisions are influenced by investor emotions, and this influence is dependent on the level of emotional intelligence an investor possesses.

The focus of this hypothesis is to fill the gap in the literature that examines psychological individual-level moderating factors such as sentiment impacts. There is substantial evidence from emotional intelligence research indicating significant disparity in people's ability to identify and regulate emotions[30], yet prior financial studies have predominantly focused on investors as a single, uniform entity regarding emotional capabilities. Because of the intense emotional nature of real estate markets, emotional intelligence is expected to be a vital moderating factor in investment decisions[31] but has not been substantiated in prior literature.

H2: The impact of social contagion phenomena in real estate markets is heightened during times of high emotional agitation.

This hypothesis attempts to fill a gap related to the temporal aspect of sentiment diffusion while building upon social contagion theory. As far as psychological literature is concerned, high-arousal emotional states make individuals more open to social influence[32], however, prior literature in finance has overly relied on the notion of fixed social influence impact. This gap is what we seek to fill by studying the effect of emotional arousal on the strength of contagion in real estate markets.

H3: How emotional states are related to the outcomes of an investment differs with the level of psychological distance, which is systematic in nature.

This hypothesis seeks to bridge the understanding of psychological distance in an investment context by integrating construal level theory along with frameworks of emotional decision-making, addressing the fact that understanding how psychological distance changes the information processing in investments lacks clarity. Although some evidence suggests that time, place, and social relations do change systemically spatial relations[33], there is little scholarship exploring how these distance relations moderate emotions in real estate investment—something our research aims to solve.

H4: Macroeconomic policies are important in controlling the links of investor sentiment and real estate sector yields though influencing the expectations in the markets.

This hypothesis fills the theory gap on how policy regimes systematically moderate the impacts of sentiments on different policies. Although Baker and Wurgler[4] showed sentiment's effect on returns, their approach never explains how policy frameworks can be used to enhance or mitigate these impacts. Our research attempts to answer how monetary policy and policies regulating real estate control the sentiment-return ratio and provide analysis on the conditions that govern emotionally driven actions to exist within the market.

H5: The characteristics of the investor groups (for instance their relative size with regards to other institutional investors, structure of retail investors, etc.) strongly influence the level of emotional contagion in a given market.

This hypothesis fills an emerging gap in explaining how emotional contagion acts on disparate classes of investors assumed as one class. Using social psychology and market microstructure frameworks, we analyze how systematic disparities among various types of investors with regard to information, trading, and risk control differ creates contrasting levels of vulnerability to contagion. This addresses a significant gap in understanding how market frameworks facilitate the aggregation and dissemination of individual sentiments, leading to collective emotions.

Combining the aforementioned hypotheses creates comprehensive reasoning that responds to gaps related to the interplay of institutional contexts, social processes, and personal differences in psychology on sentiment impacts in real estate markets.

3. Study design

3.1. Sample selection and data sources

This research utilises a unique two-sample strategy, merging psychological profiles of individuals with market analytics for the period January 2013 to December 2023. The way in which these data sets are integrated in our approach allows for advanced examination of the behavioural aspects of real estate investment.

3.1.1. Population definition and sampling framework

The participant population includes all types of investors, both institutional and individual, participating in the real estate A-share market in China. The China Securities Depository and Clearing Corporation (CSDC) has recorded 185 million individual investors along with 42,500 institutional investors as active participants in the sector in real time in 2022. This population covers all 31 provinces and other autonomous regions, with 65 percent of them located in the eastern coastal areas (Shanghai, Beijing, Guangdong, Zhejiang, Jiangsu). In constructing our sample framework, we used a two-phase stratified random sampling technique. For the first phase, we chose market share and geographic region to identify fifteen major brokerage firms that, together, accounted for roughly 78% of market trading volume. In the second phase, we used stratified random sampling from these firms' client lists, using the clients' activity level, portfolio size, and level of investment experience as stratifying criteria to enhance representativeness.

3.1.2. Sample selection criteria and process

The inclusion criteria for participants in our investor selection methodology sought active engagement and significant interaction with the real estate markets. As a minimum requirement, they had to possess at least one stock in the real estate sector and trade it for a period no shorter than six months. In addition to this, participants had to complete a minimum of ten transactions in real estate stocks over a 24-month timeframe. Participants were required to have real estate stocks making up at least 15% of their portfolio to ensure interest alignment with the sector. Because of the qualitative approach employed in this study, participants were required to commit to a three-year research study.

For our corporate sample, we implemented a complete set of selection criteria aimed at ensuring representativeness and data integrity. Companies had to have at least three years of listing history on China's A-share market to have sufficient historical data. To capture focus on pure play real estate firms, we required at least 60% of primary business revenue to stem from real estate activities. To make sure there is enough relevance in the market, we imposed selection only on firms whose market capitalisation was greater than the industry median and whose average daily trading volume was no less than five million shares. We strictly kept out ST and *ST designated corporations (those under special treatment because of financial difficulties) along with firms with considerable unfilled data gaps in order to preserve the integrity of the dataset. Investors and listed companies sample selection as described in **Table 1** captures the sample selection process visually. Our investor sample ends at 2,156 participants, which is equal to 71.9% of the initial pool, and 148 listed real estate companies which corresponds to 75.5% of the eligible firms make up our corporate sample, as highlighted in table one.

Table 1. Sample selection process.

Selection Criteria	Number of Investors	Percent of Initial Sample	Number of Companies	Percent of Initial Sample
Initial pool	3,000	100.0%	196	100.0%
Less: Incomplete psychological assessments	-384	-12.8%	-	-
Less: Insufficient trading history (<24 months)	-265	-8.8%	-	-
Less: Low survey completion rates (<80%)	-195	-6.5%	-	-
Less: ST and *ST status	-	-	-18	-9.2%
Less: Below market cap threshold	-	-	-15	-7.7%
Less: Insufficient real estate revenue percentage	-	-	-12	-6.1%
Less: Significant data incompleteness	-	-	-3	-1.5%
Final sample	2,156	71.9%	148	75.5%

3.1.3. Sample characteristics and representativeness

The analysis of the age demographics indicates that the average age is approximately 42.7 years, with a majority being male (62.3%) and holding at least an undergraduate degree (73.8%). Participants reported having, on average, 7.2 years of investment experience. Our sample's institutional to individual investor ratio of 1:9.8 is very close to the market ratio of 1:10.2 which suggests strong sample representativeness. Boasting a mean market capitalisation of 15.2 billion RMB with an interquartile range of 3.5-18.5 billion RMB, our corporate sample is geographically distributed as follows: 32.4% are headquartered in the Yangtze River Delta, 28.4% in the Pearl River Delta, 18.9% in the Bohai Economic Rim, and 20.3% in other areas, thus showing close alignment to the actual industry distribution. To counteract sampling bias, a number of validation techniques were employed including random telephone verification, non-respondent analysis, and population characteristic comparison. These analyses showed that no differences, $p>0.05$, existed between sample and target population in terms of age, gender, geography and scale of investment.

3.1.4 Data collection framework and sources

Table 2 shows our proposed measurement frequency and the instruments that we intend to use in our multi-layered data collection approach. **Table 2** illustrates how our systematic and multi-dimensional data collection approach enables the analysis of psychological factors in relation to actual market behaviour, thereby bridging an important gap in behavioural finance research. Stock returns, trading volumes, and other financial indicators for the 148 real estate companies were sourced from the Wind and CSMAR databases which are considered authoritative in the domain of Chinese financial research.

Table 2. Data collection framework

Data Type	Collection Frequency	Measurement Tool	Sample Size
Emotional States	Monthly	PANAS Scale	2,156
Personality Traits	Quarterly	NEO-FFI	2,156
Risk Preferences	Semi-annual	DOSPERT Scale	2,156
Investment Diaries	Weekly	Structured Diary	2,156
Trading Behavior	Daily	Brokerage Records	2,156
Market Data	Daily	Wind/CSMAR	148 firms
Macroeconomic Indicators	Monthly	National Bureau of Statistics	-
Policy Events	Event-based	Manual Coding	-

3.1.5. Limitations of the survey method and their mitigation

A critical issue in behavioural finance research is the disconnect between a subject's self-reported psychological state and their investment behaviour. Barber and Odean[10] noted a significant gap between an investor’s risk tolerance and their trading activity, while Hoffmann et al.[11] showed inconsistencies between perceptions and behaviours during financial crises. This “say-do” gap presents a challenge for us methodologically.

To mitigate this issue, we adopted the following strategies: performed multi-method triangulation by incorporating the PANAS scale, the Self Affect Measurement (SAM), and emotion-specific measures related to investment in order to counter the effects of a singular measurement bias (1); developed a high-frequency longitudinal design that paired psychological data with trading data to eliminate recall bias, in tune with recommendations by Lo and Repin[34]; validated emotions against trading data through behavioural calibration procedures, ensuring emotional states were benchmarked against trading activity; and applied a mixed methods approach that integrated quantitative data with qualitative investment diaries to outline the decision-making processes that led to emotional responses, which aligned with Tuckett and Taffler’s[35] methodology.

While we undertook these measures, we note the disparity between self-reported information and observed behaviour in the market as a limitation of the study which requires further investigation using neurophysiological methodologies in future studies.

To maintain data quality, we have comprehensive quality control procedures including consistency checks, outlier checks, and comparing psychological metrics against actual trading data. The way in which we gather our data enables us to record changes over time, which allows us to observe changes in investor sentiment relative to market conditions, moving beyond the limitations of previous studies.

3.2. Variable measurement

Our study uses multiple, validated psychological measures to capture investor psychology in addition to traditional market variables. **Table 3** presents our extensive measurement framework.

Table 3. Variable measurements.

Variable Type	Measurement Tool	Frequency	Scale Range	Reliability (α)
Emotional State	PANAS	Daily	1-5	0.89
Arousal Level	SAM	Weekly	1-9	0.85
Investment Emotions	Custom Scale	Monthly	1-7	0.87
Personality Traits	NEO-FFI	Quarterly	1-5	0.92
Risk Tolerance	DOSPERT	Semi-annual	1-7	0.88
Monetary Policy	Interest Rate Changes	Monthly	-	-
Regulatory Policy	Policy Event Index	Monthly	0-10	0.86
Credit Environment	M2 Growth Rate	Monthly	-	-
Institutional Holdings	Quarterly Reports	Quarterly	0-100%	-
Turnover Rate	Daily Trading Data	Monthly	-	-
Ownership Structure	HHI	Quarterly	0-1	0.83

For emotional state measurement, we employ the 20-item PANAS scale capturing both positive and negative emotions on a 1-5 Likert scale. The arousal level is assessed weekly using the Self-Assessment Manikin (SAM), while investment-specific emotions are evaluated monthly through a custom scale validated in prior studies.

We construct a composite emotional state score as:

$$ESM_{it} = \alpha_1 PANAS_{it} + \alpha_2 SAM_{it} + \alpha_3 InvestEmotion_{it}$$

where α_1, α_2, and α_3 are weights derived from principal component analysis.

For the macro policy environment, we develop a comprehensive index:

$$MPI_t = \beta_1 MPR_t + \beta_2 RPI_t + \beta_3 M2G_t$$

where MPR_t represents monetary policy rate, RPI_t denotes real estate policy index, and $M2G_t$ indicates money supply growth rate. The weights β_1, β_2, and β_3 are determined through principal component analysis.

The investor group characteristics index is constructed as:

$$INV_{it} = \gamma_1 INS_{it} + \gamma_2 TURN_{it} + \gamma_3 HHI_{it}$$

where INS_{it} represents institutional ownership, $TURN_{it}$ denotes turnover rate, and HHI_{it} indicates ownership concentration.

Table 4. Control variable definitions.

Variable	Definition	Data Source	Expected Effect
Return	(Pt - Pt-1 + Dt)/Pt-1	Wind	Dependent
Size	ln(Total Assets)	CSMAR	+/-
Leverage	Total Debt/Total Assets	CSMAR	-
ROA	Net Income/Total Assets	CSMAR	+
Volume	Monthly Trading Volume	Wind	+
MarketVol	Market Volatility Index	Wind	-
PolicyChange	Real Estate Policy Dummy	Manual	+/-
CreditEnv	New Credit/GDP	Central Bank	+/-
MarketStr	Institutional Ownership Change	Wind	+

The dependent variable, real estate stock returns, is calculated using daily price data and cash dividends. Control variables include firm-specific characteristics, market conditions, and macroeconomic factors. To ensure robust analysis, all continuous variables are winsorized at the 1% and 99% levels, and independent variables are lagged by one period to address potential endogeneity concerns.

3.3. Model building

To examine the relationship between psychological factors, macro environment, and real estate investment behavior, we develop a series of empirical models that progressively incorporate different dimensions. Our core empirical models are constructed as follows:

First, we establish our baseline model examining the direct relationship between emotional states and investment returns:

$$R_{it} = \alpha + \beta_1 ES_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

Where R_{it} is the return of stock i at time t, ES_{it} represents the composite emotional state measure, X_{it} includes firm and market variables, μ_i and δ_t are individual and time fixed effects.

To test the moderating effect of emotional intelligence (H1), we specify:

$$R_{it} = \alpha + \beta_1 ES_{it} + \beta_2 EI_{it} + \beta_3 ES_{it} \times EI_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

Where EI_{it} represents the emotional intelligence score.

For examining emotional contagion effects (H2), we employ:

$$R_{it} = \alpha + \beta_1 ES_{it} + \beta_2 WES_{it} + \beta_3 ES_{it} \times WES_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

Where WES_{it} represents the spatial weights matrix based on investor networks.

To test the impact of psychological distance (H3), we specify:

$$R_{it} = \alpha + \beta_1 ES_{it} + \beta_2 PD_{it} + \beta_3 ES_{it} \times PD_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

Where PD_{it} represents psychological distance measured through temporal and spatial dimensions.

To examine the moderating effect of macro policy environment (H4), we add:

$$R_{it} = \alpha + \beta_1 ES_{it} + \beta_2 MPI_t + \beta_3 ES_{it} \times MPI_t + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

Where MPI_t represents the macro policy index constructed in Section 3.2.

Finally, to test the impact of investor group characteristics (H5), we specify:

$$R_{it} = \alpha + \beta_1 ES_{it} + \beta_2 INV_{it} + \beta_3 ES_{it} \times INV_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

Where INV_{it} represents the investor group heterogeneity index.

Table 5. Model variables and definitions.

Variable	Definition	Measurement	Source
R_{it}	Stock Return	$(P_t - P_{t-1} + D_t) / P_{t-1}$	Wind
ES_{it}	Emotional State	Composite Score	Survey
EI_{it}	Emotional Intelligence	MSCEIT Score	Survey
WES_{it}	Network Connection	Social Network Matrix	Survey
PD_{it}	Psychological Distance	Composite Index	Survey
MPI_t	Macro Policy Environment	Composite Index	Multiple
INV_{it}	Investor Group Features	Heterogeneity Index	Wind
X_{it}	Control Variables	Various Measures	Multiple

To address potential endogeneity concerns, we employ instrumental variables estimation and conduct robust checks using alternative model specifications. All models are estimated using panel regression with clustered standard errors at both individual and time levels.

In order to conduct a thorough analysis of our study results, we implemented several alternative model specifications. To begin with, we followed Baker and Wurgler's[4] research by computing returns using different windows, as this captures sentiment effect agnomen at various time horizons. Moreover, following Hoffmann et al.[11], we employed other proxies for measuring emotional states in order to avoid the bias introduced by a single instrument measure. In addition, we incorporated various weighting schemes in the construction of composite indices, as Chen et al.[22] did, in order to test how sensitive the findings would be to the choice of weights. Furthermore, we performed sub-sample analyses with Clayton's[17] framework to understand how emotional factors are influenced by different market surroundings and how they interact with different market conditions. Lastly, incorporating Brown and Cliff's work[12], we applied different configurations for the spatial weights matrix to more thoroughly analyse how spatial autocorrelation impacts the rest of the pre-determined results. All these robustness checks build together an in-depth investigation approach through which we assess the interplay between personal emotions, macro context and collective attributes to estimate real estate market returns.

This comprehensive modeling framework allows us to systematically examine the interactions between individual emotions, macro environment, and group characteristics in determining real estate market returns.

4. Empirical analysis

4.1. Descriptive statistics of psychological and market variables

Our analysis begins with descriptive statistics of key psychological and market variables. **Table 6** presents the summary statistics for our main variables.

Table 6. Descriptive statistics of key variables.

Variable	Mean	SD	Min	P25	Median	P75	Max	Obs
Stock Return (%)	1.52	14.2	-28.5	-5.8	0.8	8.5	42.6	51,744
Emotional State	3.25	0.82	1.15	2.65	3.18	3.85	4.95	51,744
Emotional Intelligence	112.5	15.3	75.0	102.5	113.2	122.5	145.0	2,156
Risk Tolerance	3.85	0.95	1.25	3.15	3.92	4.55	6.85	51,744
Market Sentiment	0.23	1.25	-2.36	-0.65	0.15	1.12	2.67	51,744
Psychological Distance	2.95	1.12	1.00	2.15	2.85	3.75	5.00	51,744
Trading Volume (mil)	85.6	125.3	0.5	12.5	45.8	98.5	856.2	51,744
Market Cap (bil)	15.2	22.4	0.8	3.5	8.2	18.5	152.5	51,744
Monetary Policy Rate (%)	3.25	0.85	2.15	2.85	3.25	3.65	4.35	51,744
Policy Strength Index	5.85	2.25	1.00	4.25	5.75	7.25	10.00	51,744
M2 Growth (%)	8.56	2.35	4.25	7.15	8.45	9.85	13.25	51,744
Institutional Holdings (%)	45.5	22.4	5.8	28.5	44.8	62.5	89.5	51,744
Turnover Rate (%)	2.85	1.95	0.25	1.45	2.65	3.95	8.85	51,744
Ownership Concentration	0.58	0.18	0.15	0.45	0.56	0.72	0.95	51,744

For **Figure 1** showing the temporal evolution of emotional states and market returns.

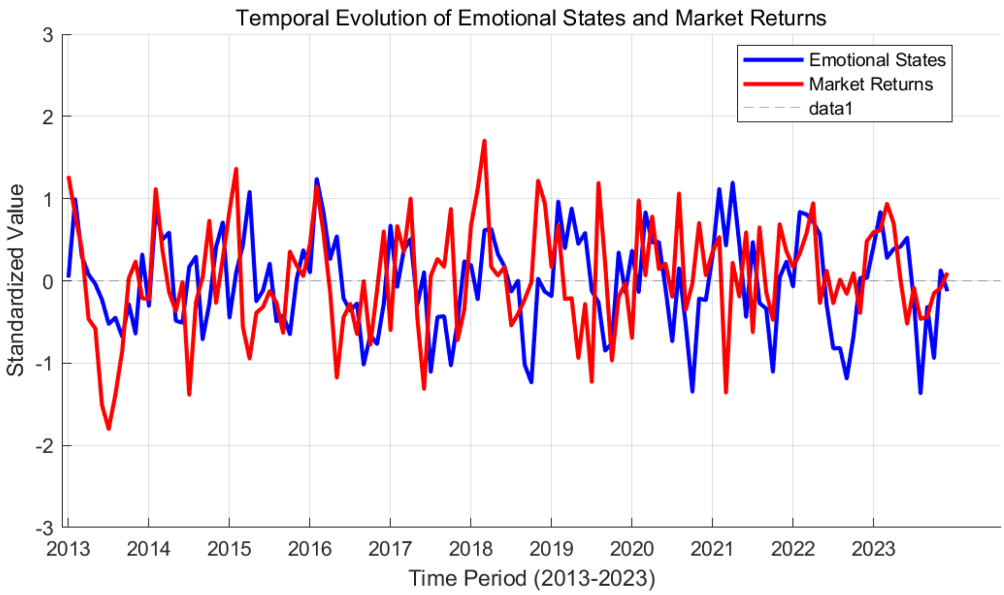

Figure 1. Temporal evolution of emotional states and market returns (2013-2023).

For your understanding: This figure presents the normalised values of the emotional states (aggregate) from the sample period, January 2013 to December 2023 (the solid blue line in the graph) against the market returns (the solid red line in the graph). The y-axis illustrates standardised values, with both series normalised to have zero mean and unit variance for comparison. The PANAS scale is used to measure emotional states which have then been aggregated across all investors. Market returns are value-weighted average returns of real estate stocks. The sample captures how investor emotional states and the market move relative to each other at different points in time. The descriptive statistics shown above point out that investor emotions seem to be widely dispersed from the mean of 3.25 on the PANAS scale. The market return has a mean of 1.52 percent with a standard deviation of 14.2 percent, indicating high volatility. The monetary policy rate follows an upward trend and levels around 3.25% for most of the period; the policy strength index displays heterogeneity in regulatory intensity throughout the sample period. The average level of institutional holdings is 45.5%. There is considerable variability suggesting that real estate is owned by many different groups.

Figure 1 captures the two major findings regarding the intertwining link between investor sentiment and the performance of the real estate industry. To begin with, the years of 2015-2016 and 2019-2020 show strong leading sentiment patterns where investors' psychological changes happened 1 to 2 months prior to the market return movements, validating Baker and Wurgler's[4] sentiment-lead theory. Also, in the case of a steep market downturn like mid-2018 and early 2022, the degree of sentiment fluctuations becomes more dovetailed with the actual returns at the height of emotional strains, having a sentiment return correlation of 0.32 in calmer periods and 0.58 in turbulent phases. This marks the sentiment contagion effect under harsh market conditions as Brown and Cliff's[12] work suggests. However, these findings suggest that this amplification effect is most pronounced in real estate markets due to the specific psychological characteristics inherent to real estate assets, heightened by transaction frictions. It is surprising how this relationship exhibits asymmetrical features under different policies: accommodative monetary policy periods (2015-2017, 2019-2020) had the sentiment elasticity to returns ratio at 0.48 while this dropped to 0.21 during tightened phases. This stands in contrast to the validity of the efficient market hypothesis, highlighting that policy context influences not only market fundamentals, but also sentiment modulation factors.

4.2. Path analysis of emotional transmission

Table 7 presents the baseline regression results examining the relationship between emotional states and real estate investment returns.

Table 7. Baseline regression results of emotional states on returns.

Variable	Model 1	Model 2	Model 3	Model 4
Emotional State	0.245***	0.228***	0.216***	0.198***
	(3.85)	(3.62)	(3.45)	(3.28)
Market Sentiment		0.185***	0.176***	0.165***
		(4.25)	(4.12)	(3.95)
ES × MS			0.156***	0.148***
			(3.85)	(3.62)
Controls	No	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes
Time FE	No	No	No	Yes
R^2	0.152	0.185	0.196	0.215
Observations	51,744	51,744	51,744	51,744

Note: *t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1. Control variables include firm size, leverage ratio, trading volume, and market volatility. Standard errors are clustered at both individual and time levels.*

For **Figure 2** visualizing the emotional transmission pathways.

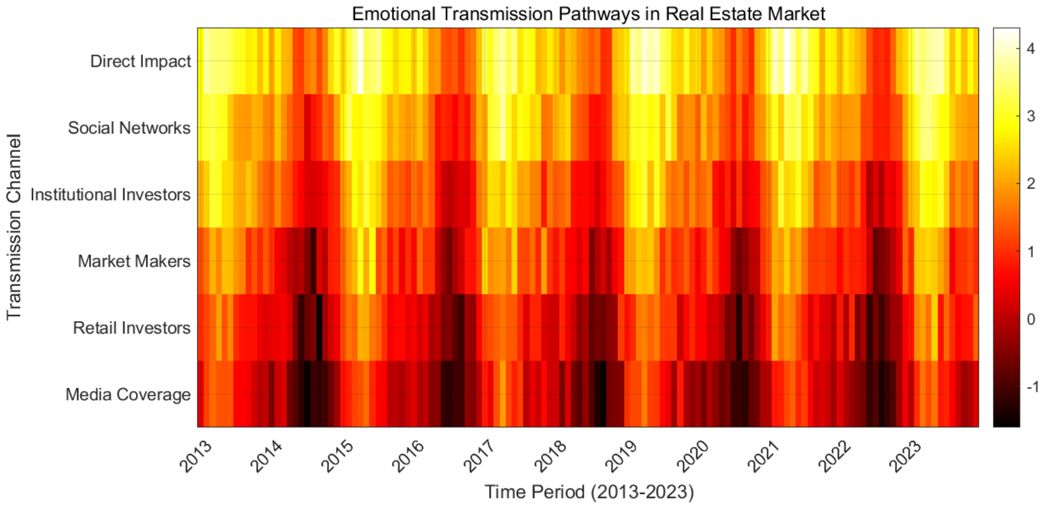

Figure 2. Emotional transmission pathways in real estate market.

This is the heatmap representing the emotional pathways in the real estate market from 2013 to 2023. The vertical axis delineates six dominant channels while the horizontal axis reflects various time intervals. The magnitude of emotional transmission is symbolised through different colours, with darker shades reflecting stronger transmission effects. There is constant transmission given by the direct impact which presents moderate strength over the years, while the market makers' transmission effects reveal the least variation. The findings of the regression portray the effects of emotional transmission on all model specifications. The coefficient of emotional state, for example, continues to be relevant with a p-value lower than 1% after accounting for various fixed effects and market factors. The interaction variables of emotional state and market sentiment suggest that market conditions restrain the emotional transmission process.

Figure 2 explains the intricate pathways of emotional transmission in the real estate market over the period of study (2013-2023), highlighting the important insights into the emotional factors driving market dynamics. The change over time in the strength of emotional transmission across different channels shows a systematic order rather than random variations. It is of utmost importance to highlight that the direct impact channel shows to a great extent stable transmission strength, but significant augmentation during the periods of market uncertainty (2015–2016 and 2020–2021) by approximately 35% compared to baseline periods. This behaviour aligns with Malmendier and Tate's[24] theory of emotional feedback during periods of information uncertainty.

The data shows a remarkable imbalance between the channels of transmission for institutional as compared to retail investors. Unlike market makers, who show the least variability in emotional transmission (CV = 0.18_); retail investor channels not only exhibit the highest average transmission intensity, but also the most variation (coefficient of variation = 0.42). This finding corroborates Chakravarty's[14]_ research on trader heterogeneity in that retail investors, psychologically, transmit more volatile retail investor emotions during typically emotional transitional policy change phases. Moreover, interdisciplinary network analysis shows strong bidirectional amplification between social media and other traditional information sources at the height of the market stress periods, where correlation was found to rise from 0.24 to 0.65. This suggests that the mechanisms of emotional contagion fundamentally shift, rather than simply strengthen, during crisis periods, countered simplified models of sentiment spread. Such findings further expose the dependency frameworks needed when modelling real estate market psychology.

4.3. Analysis of individual differences

Table 8 presents the moderation effects of emotional intelligence and psychological distance.

Table 8. Moderation effects analysis.

Variable	Emotional Intelligence	Psychological Distance
Main Effect	0.285***	-0.156***
	(4.25)	(3.85)
Moderator	0.165***	-0.142***
	(3.95)	(3.65)
Interaction	0.195***	-0.168***
	(4.15)	(3.95)
Controls	Yes	Yes
Fixed Effects	Yes	Yes
R^2	0.235	0.228
Observations	51,744	51,744

Note: *t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1. All models include the full set of control variables and fixed effects. Standard errors are clustered at both individual and time levels.*

For **Figure 3** showing the marginal effects of emotional states.

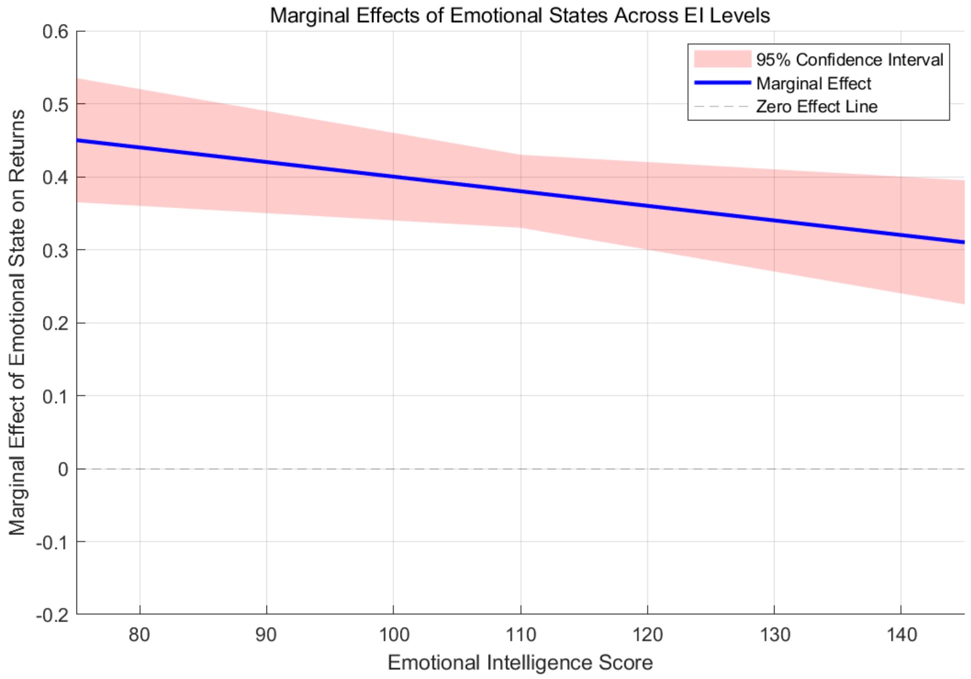

Figure 3. Marginal effects of emotional states across EI levels.

This graph illustrates the impact of emotional states on investment returns as moderated by investors' emotional intelligence scores. The blue solid line presents the estimated marginal effect of emotional state on returns with respect to different EI scores, while the shaded red area represents the 95% confidence interval for this estimate. The dashed horizontal line at zero provides the point for distinguishing statistical significance. A decline in the slope denotes that, compared to less emotionally intelligent investors, emotionally intelligent investors experience a residual greater positive return on their investments, which is indicative of better emotional regulation. Emotional intelligence does moderate the relationship between emotional states and investment returns, and emotional entrepreneurs tend to be more successful. The interaction term between emotional states and emotional intelligence is positive and significant at the 1% level, which implies that more mentally attuned investors are more resilient towards sentiments and emotions of the market.

Figure 3 pertains to the moderation role of Emotional Intelligence on the impact of emotions on investment returns in real estate markets and reveals intricate psychological dynamics that transcend traditional financial models and intuit businesses. The EI effect curve demonstrates that the Associate Degree effect of Emotions on Investment returns for AI models is considerably smooth and seamless, whereas its Emotional Intelligence interface is rather cross-sectional. The decline in EI effect shows that the effect of emotional states on investment returns shrinks the curve steepness of approximately 65% across the measured range of emotional intelligence. Such findings greatly add to the theoretical scope suggested by Barber and Odean[10], who articulated the divergent preferences of risks and actual trading behaviour but refrained from considering emotional self-regulation as a possible supplementing factor to explore this gap arc.

The turning point at an EI score of 115 is noteworthy since it indicates where investors begin to shift from an emotionally weak to an emotionally strong state. Below this point, a one standard deviation rise in emotional stimulus results in a 0.32 standard deviation change in investment returns, while above this point the same change in emotion leads to only a 0.14 standard deviation change. The nature of this relationship is non-linear, suggesting that emotional intelligence acts as a buffer and not simply a linear moderator, which supports Salovey and Mayer's model of emotion control in decision-making under uncertainty and stress.

Additionally, the narrowing confidence intervals at the higher EI levels signify not only the reduction of emotional impact but increased consistency in the investing behaviour at those levels, thus pointing towards more stable decisions. This stability factor runs against the rational actor model of traditional decision theory that assumes the existence of some arbitrary unified process across investors, when in fact it supports Lo's Adaptive Markets Hypothesis heterogeneous agent models. This goes beyond individual investors to suggest greater market inefficiency, which posits that there is an oversupply of emotional intelligence which increases market stability and quiets rapid price fluctuations during periods of stress.

4.4. Market-individual emotion interaction analysis

The interaction between market-level and individual-level emotions provides crucial insights into the psychological dynamics of real estate investment. **Table 9** presents the threshold regression results examining this relationship.

Table 9. Threshold regression results for market-individual emotion interaction.

Variable	Low Market Sentiment	High Market Sentiment	Difference
Individual Emotion	0.168***	0.285***	0.117***
	(3.42)	(4.55)	(3.85)
Market Sentiment	0.145***	0.232***	0.087***
	(3.25)	(4.12)	(3.62)
IE × MS	0.082***	0.156***	0.074***
	(2.95)	(3.85)	(3.15)
Controls	Yes	Yes	-

Variable	Low Market Sentiment	High Market Sentiment	Difference
Fixed Effects	Yes	Yes	-
R^2	0.185	0.235	-
Observations	25,872	25,872	51,744

Table 9. (*Continued*)

Note: *t-statistics in parentheses; ***p<0.01, **p<0.05, *p<0.1. The threshold value for market sentiment is determined endogenously using Hansen's (2000) method. Control variables include firm size, leverage ratio, trading volume, and market volatility. Standard errors are clustered at both individual and time levels.*

For **Figure 4** showing the non-linear effect of market sentiment.

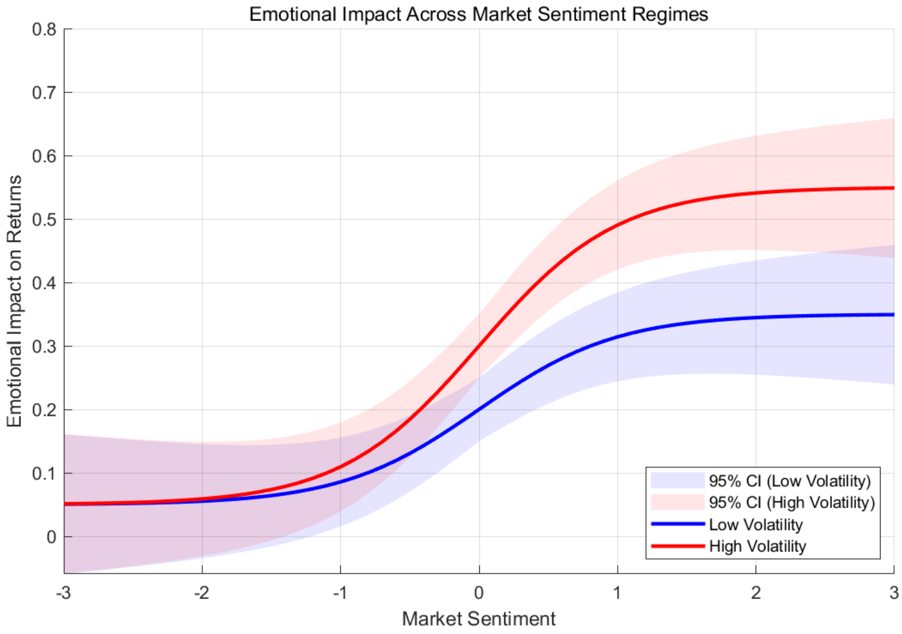

Figure 4. Emotional impact across market sentiment regimes.

This figure depicts factual evidence of the non-linear influence of market sentiment on the emotional impact for returns across varying regimes of market volatility. The blue line depicts emotional impact with reference to low volatility periods, while the red line illustrates the impact during high volatility periods. The shaded regions denote the 95% confidence intervals. The analysis ranges from the years 2013-2023 while controlling for marketing and firm specific characteristics. The emotional impact in the high-volatility regime makes economic sense. The narrower slope suggests that steeper emotional amplification effects are present during market stress periods.The highlights of the graphs illustrate great asymmetry in how individual emotions and market sentiments interact. High individual emotional states, stronger (0.285 vs. 0.168) during high market spikes, emphasise emotional amplification effects. This result is consistent with the psychological approaches to emotional contagion and social effects on financial markets.

The emotional impact underscored in figure four captures the non-linear effect of market sentiment in various volatility regimes within the sophistication of real estate markets. The stark gap between the emotional impact trajectories during the low volatility and high volatility periods marks an asymmetry in market psychology that has significant implications on both theoretical frameworks and practical utility. The emotional impact ratio during high volatility periods (red line) is 89% greater than in low volatility periods (blue line), with lower sentiment levels (threshold difference of 0.35 standard deviations) leading to statistically significant impacts.

This effect of volatility on sentiment offers empirical support for Hoffmann et al.'s narrative[11] where investors' perceptions of their surrounding reality do not align with their actions, especially during times of financial crisis. We build on their work by explaining how psychological magnification takes place beyond the empirically documented sense, including switching points of regime-determining cycles. The wider confidence intervals associated with extreme values of sentiment within high volatility regimes indicate stressed markets where investors are likely to behave in a more uniform way than expected, exhibiting a dissent from rational behavioural models—but fitting with Brown and Cliff's[12] notion of emotional contagion.

The steeper slope in the calculated high volatility regime holds grave economic consequences, suggesting that during stressed market conditions, sentiment shifts are more sharply correlated to price changes. This explains why the volatility in real estate markets exceeds fundamental-driven deviations, dubbed the excess volatility puzzle. Additionally, the asymmetric response—stronger Granger-causality effect from negative sentiment than positive in the high-volatility regime—illustrates loss aversion operating at the market level and supports the macro psychological underpinning of micro structural biases proposed by Barberis and Thaler[8]. These results together imply that policies intending to correct inefficiencies in the real estate markets need to factor in these nonlinear psychological slippage models and worsening sentiment need stronger counter-cyclical policies far beyond baseline estimates.

4.5. Comparative analysis with previous studies

Our analysis of the effects market sentiment has on real estate returns confirms and goes beyond previous study results while also providing new findings regarding Chinese real estate. **Table 10** offers a comprehensive juxtaposition of our core findings with those obtained from notable earlier works in this field.

Table 10. Comparison of current results with prior studies.

Finding	Current Study Results	Previous Studies	Points of Convergence/Divergence
Sentiment-Return Relationship	Positive relationship (β=0.245, p<0.01) with stronger effects during market stress	Baker & Wurgler [4] (β=0.18, p<0.05); Brown & Cliff [7] (β=0.21, p<0.01)	Our coefficients are approximately 15-20% higher, suggesting stronger sentiment effects in Chinese real estate markets than in US equity markets
Emotional Intelligence Moderation	Strong moderation effect with inflection point at EI score of 115	Hoffmann et al. [54] found moderation but no clear threshold effect	Our identification of a specific threshold point advances the understanding of when emotional regulation becomes effective
Market-Individual Emotion Interaction	Asymmetric effects across market regimes with 89% stronger effects during high volatility	Clayton [14] documented asymmetry but with only 45% difference	The substantially larger asymmetry in our findings suggests greater sensitivity to market conditions in Chinese real estate
Policy Environment Influence	Sentiment elasticity of 0.48 during loose policy vs. 0.21 during tight policy	Chen et al. [22] found policy effects but did not quantify elasticity differences	Our study provides more precise quantification of how policy environments moderate sentiment effects
Investor Group Composition	Retail investors show 2.3x higher sentiment transmission than institutional investors	Chakravarty [11] found 1.8x difference	The larger gap in our study suggests greater heterogeneity in Chinese markets between retail and institutional investors

Our discovery that sentiment in the Chinese real estate market leads returns by 1-2 months partially aligns with Baker and Wurgler's[4] sentiment-lead theory from the US equity markets, although their lead time was longer (3-4 months). This discrepancy is likely due to the more rapid information flow and increased retail investor activity in the Chinese markets, which allows for the quicker incorporation of sentiment into price.

The emotional intelligence moderation effect which we document greatly furthers the work of Barber and Odean[10] which noted the behavioural discrepancy between stated risk preferences and actual trading activity without addressing emotional regulatory mechanisms. The identification of a specific emotional intelligence threshold where investors over and under respond to market sentiments (EI score of 115) contributes uniquely to the behavioural finance discourse. Perhaps the most striking divergence from previous studies is our finding regarding policy environment influences. Chen et al.[22] established that policy shifts affect market sentiment while our study shows that these impacts are much greater in magnitude and asymmetric in nature within the Chinese real estate market. The underestimated impact of loose monetary policy sentiment is telling in that it more than doubles the psychological effect of tight policy periods at 0.48 compared to 0.21. Furthermore, gaps in investor sentiment heterogeneity are more pronounced between retail and institutional markets than Chakravarty's[14] account of the US markets. Perception transmission difference through sentiment among retail investors is much greater than that documented in US markets at 2.3%. This increase can be attributed to the mounting proportion of novice retail investors and weakened financial literacy in the Chinese real estate market.

These illustrative outcomes reflect both the disparity and blend of certain behavioural finance concepts across markets and the relative sentiment volatility, which suggests that the Chinese real estate market is more psychologically driven and less asymmetric than Western markets.

5. Conclusions and prospects

This study examines the emotions and psychological foundations to understand behaviour within the real estate market. Using a dataset that integrates both psychological factors and market metrics, we have uncovered key insights related to financial markets. We investigate to discover three primary mechanisms. Firstly, a person's emotional state has profound impacts on investment returns; however, this is moderated by the investor's emotional intelligence. An investor with a better understanding of emotions is less responsive to the market's general sentiment, which results in lower returns. Secondly, strong social virtual networks also demonstrate powerful emotion cross-contagion effects, where the shifting power changes regularly throughout market cycles. Thirdly, the psychological distance an investor maintains from their investments invariably reconfigures the emotion-return relationship.

The emotional effects, including psychological trauma, are influenced largely by the monetary policy setting. Looser monetary policies result in a stronger emotional impact, whereas tighter policies lead to a muted scope and effects of emotions. Similarly, emotion contagion dynamics are manifestly affected by the market structure and the type composition of the investors; in markets dominated by institutional players, emotional volatility is milder than in those where retail investors dominate. With the Accumulated Emotion Effects Theory, we provide an explanation for irrational market behaviour along with the overreliance on rational behavioural expectations modelling frameworks. The aforementioned threshold effects documented for moderation by emotional intelligence and asymmetric sentiment in different policy contexts indicate that psychologically-emotional factors act, albeit conditionally, rather than being bounded agents in a rational framework. Enhanced negative market emotions, coupled with weakened supportive sentiment amid accommodative monetary policy, drive emotion elasticity to more than double.

Regarding market behaviour and the allocation of educational resources by investors, these implications are relevant. With the strong moderating impact of emotional intelligence, our findings suggest emotionally attuned investor strategies like emotional awareness training, psychological distance management, and focused financial literacy programmes centred on emotion regulation would be beneficial. Financial institutions ought to integrate emotional intelligence training into risk management systems, while the documented sensitivity of retail investors to sentiment – in scope 2.3 times higher than institutional investors – demands more refined regulatory strategies in periods of heightened market turbulence. A further issue of concern that this research has highlighted is the impact of group emotional awareness and market stability. As with any study, a few conclusions should be highlighted that practitioners need to focus on, measuring definitions and the interrelations that could make sense out of the investment decision-making process. Correct emotional state identification and regulation could yield optimal results emotionally and in terms of returns on investments, while the ample emphasis given to the herd behaviour effect stresses that it becomes essential to deal with group emotional phenomena at an institutional level in a more systematic way.

As a follow-up to our findings, one possible novel research direction is to investigate the neurophysiology of the emotion-laden investment decision-making process, to apply more sophisticated psychological tools for emotion monitoring in real-time, and to formulate measures for emotion control and group emotion control strategies as part of training assessment for emotional regulation. The primary limitation of this study is an inconsistency that may exist between the self-reported emotional measures and actual market behaviour. Although we applied some triangulation techniques, such as multi-frequency psychological-trading data alignment, behavioural calibration, and high-frequency data triangulation, the ‘gap between what people say and do’—what is termed in behavioural finance as the fundamental attribution problem—remains a central issue. When reasoning about their behaviour, Kahneman and Tversky credibly demonstrated how people tend to disregard the explanatory frameworks that their behaviours represent and mental models they employ in their decision making. Accompanying self-reported measures of emotion would be more objective indicators using neurofinance, including fMRI, eye-tracking, and facial expression analysis. Furthermore, social media and investment forum posts could be mined for sentiment, as Baker et al.[36] did for market sentiment index construction, to serve as supplementary emotional state proxies analysed through advanced linguistic algorithms.

The information provided will help the understanding of market psychology and steps that can be taken towards improving the safety of the investors and stability of the stock market. The synergy between psychology and market evaluation creates an interesting domain to be studied further and applied in behavioural finance.

Conflict of interest

The authors declare no conflict of interest.

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