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THE POWER OF INFLUENCE: EXAMINING THE EXTERNAL FACTORS SHAPING HERDING BEHAVIOR AMONG RETAIL INVESTORS IN THE INDIAN DERIVATIVE MARKET

LG Honey Singh[1]

Research Scholar, Ranchi University

Dr Amar Kumar Choudhary2

Associate Professor, Ranchi University

Abstract:

Behavioral biases greatly impact how investors make decisions in the market, with herding behavior being a common bias where investors imitate the actions of others. While most previous studies have focused on herding behavior in the Spot market, this investigation delves into the factors influencing herd mentality among investors in the Indian Derivative market. A customized questionnaire based on existing research was developed and distributed to active derivative investors in India using a Google Form. Through the analysis of 197 responses using Cross-Sectional analysis and Exploratory Factor Analysis, this study pinpointed several key factors that drive herding behavior: Public Information, Peer Influence, Social Group, Fear of Missing Out, Knowledge and Trust, Experiences, Under-Confidence, Professional & Broker Influence, and Social Media Influence. This research breaks new ground in understanding the factors that shape herding behavior among retail investors in the Indian Derivative Market, enhancing our comprehension of these biases. By shedding light on these determinants, the study aims to assist investors in recognizing and minimizing the effects of biases on their decision-making processes, thereby guiding them toward making more rational investment decisions.

Keywords: Herd Behavior, Derivative Market, Social Influence, Behavioral Biases, Exploratory Factor Analysis

JEL Classification: G02, G40, G41

Introduction:

Behavioral analysis of markets has been a significant field of study for practitioners and academics alike over time. Behavioral analysts in markets concentrate solely on the psychology of real market participants and how their present emotions influence market prices. This differs from traditional models of behavioral analysis, which typically blend psychological insights with neo-classical economic theory. Numerous studies demonstrated that the efficient market hypothesis and the notion of rationality in finance have significant flaws when it comes to replicating actual stock returns (Cipriani & Antonio, 2005, 2008; Drehmann, et al., 2005; Park & Sabourian, 2011, Chaudhary, A. K. (2013)). Shiller (1987) concluded that investors' emotional responses, rather than their reasoned reasoning, were what triggered the 1987 stock market crash. According to the efficient market theory, investors discount all available market information when forming rational expectations for future pricing. The efficient market hypothesis is based on the rationality assumption, but in practice, this assumption is frequently contested because observed returns in many markets exhibit "herd behavior." Herd behavior refers to a tendency among a collective to mimic the actions of others or adhere to the popular opinion, often without regard for their own knowledge or opinions (Bikhchandani & Sunil, 2000). As a result, prices diverge from their intrinsic value, which affects the stock prices' characteristics of risk and return.

Herding is a commonly employed term in studies within behavioral finance to describe the link in transactions resulting from investor engagements. When less experienced investors try to follow in the footsteps of successful investors or imitate financial gurus, this is thought to make sense because it would be more expensive to use their own information and knowledge. As noted by Nofsinger and Sias (1999) The outcome of this collective investment behavior is characterized by a cohort of traders engaging in similar market activities over an extended timeframe. In practice, this can lead to identifiable shared behavioral trends among participants, subsequently leading to communal decision-making that is both consistent and deficient (Bikhchandani et al., 1992).

In the financial landscape, the notion of the herd mentality manifests significantly portraying how investors tend to align with the judgments of a collective cohort rather than immersing themselves in fundamental and technical analysis. (Lux, 1995, Morone and Samanidou, 2007).

The practice of herding traces back to 1936 with the development of the acclaimed "General Theory" by J.M. Keynes. This theory suggests that long-term investors tend to mimic the market to safeguard their investments, while professional managers engage in herding behavior to protect their reputations and avoid conflicting actions. The study of herding behavior holds significance in research due to its intricate connection with and influence on stock prices. When investors collectively opt to invest in a particular stock, this leads to a heightened demand in the market. Fundamental-based herding typically serves a functional purpose by influencing prices, whereas imitation-based herding tends to be dysfunctional, resulting in price reversals and excessive market volatility (Bikhchandani and Sharma, 2000).

Two avenues have emerged from empirical studies of herding behavior in financial markets. According to the measure of dynamic correlations, co-movement behavior is the main focus of the first path. For example, Corsetti et al. (2005) found "some contagion, some interdependence" among Asian stock markets in their tests for financial contagion. According to Chiang et al. (2007), herding behavior predominated in the later stages of the Asian financial crisis as investors realized the full impact of the crisis and the contagion effect occurred during the early stages of the crisis. According to Boyer, et. al., (2006), they discovered a higher level of synchronization in developing stock markets when volatility is high. This suggests that contagion, rather than shifts in underlying fundamentals, plays a crucial role in the propagation of crises across the asset portfolios of global investors.

The cross-sectional correlation dispersion in stock returns as a function of extreme changes in market conditions is the subject of the second approach to studying herding behavior. Researchers predict that investors in emerging markets will exhibit herding behavior more frequently based on their observations of information asymmetry in these markets. Zhou and

Lai (2009) find that investors are more likely to herd when selling stocks than when purchasing them and that herding activity in Hong Kong's market is more common with small stocks.

Theoretical models created by Bikhchandani and Sunil (2000), Scharfstein and Stein (1990), and Devenow and Welch (1996) offer an alternative explanation for how investors evaluate information and make investment decisions. Conversely, empirical research has concentrated on evaluating herding in a variety of contexts, such as cross-country and cross-market investigations. After examining herding behavior in the stock markets of the US, Hong Kong, South Korea, Taiwan, and Japan, Chan, Cheng, and Khorana (2000) found that for the majority of their sample, there was no widespread herding activity. Hwang and Salmon (2004) and Demirer and Kutan (2006), in a more targeted research, looked at herding behavior in the stock markets of China and South Korea, respectively. The testing procedures of Gleason, Mathur, and Peterson (2004) were applied to future markets and exchange-traded funds. Mutual fund managers were asked to participate in a herding experiment conducted by Wermers (1999).

Low rates of return are linked to bearish markets. Further research is necessary because investors' actions in varying market conditions may differ in this regard. Furthermore, investor herding behavior changes in an up-and-down market, and the correlation between herding behavior and market (portfolio) return is no longer linear (Chang et al., 2000).

This paper studies the herding behavior exhibited by retail investors in the Indian derivative market and aims to identify the factors impacting the herding bias of these investors.

Literature Review:

In the spheres of economics and finance, the concept of "herding" or "herd behavior" pertains to the phenomenon where economic actors imitate the actions of others or base their decisions on the behaviors of their peers. It can be likened to a collective of market participants trading in unison (Nofsinger and Sias, 1999), investors forsaking their original evaluations to align with prevailing trends (Avery and Zemsky, 1998), mutual imitation practices (Welch, 2000), widespread consensus in analyst forecasts (DeBondt and Forbes, 1999), behaviors gravitating towards the average (Hirshleifer and Teoh, 2003), instances of correlated actions (Hwang and Salmon, 2004), groups of investors mirroring each other's moves into or out of specific securities (Sias, 2004), and similar behaviors.

Studies like Avery and Zemsky (1998) have found that in certain instances the herding behavior of investors is rational. In a study by Kingsley, et al., (2004), it was observed that active fund managers exhibit a higher tendency to follow the herd when divesting stocks, dealing with smaller stocks, and transitioning between industry sectors for investments. Similarly, Nikolaos (2020) discovered that herding behavior is more pronounced in bullish digital currency markets, particularly during exceptional circumstances, compared to regular market conditions. The incentives for parties to engage in herding or cascading are both incentives for parties to protect against or take advantage of herding or cascading by others as found by Hirshleifer and Teoh (2003). In the academic realm, it is observed that a generic communication framework among agents leads to the emergence of long tails in the stock price variation distribution, often following an exponentially truncated power law model, as explored by Cont and Bouchaud (1997).

Cipriani and Guarino (2010) on average, 2 percent (4 percent) of knowledgeable traders herd-buy (sell) on an information-event day. The percentage of knowledgeable traders that herd-buy (sell) exceeds 10% on 7% (11%) of information-event days. Significant informational inefficiencies brought about by herding equal, on average, to 4% of the asset's projected value. Gleason (2004) that investors do not herd during periods of extreme market movements using ETFs. Vo and Phan (2019) gave noteworthy proof of herding asymmetry dependent on average market liquidity. For high and medium liquidity stocks, the herd mentality is more evident. We also discover anecdotal evidence that the bidirectional effects of market liquidity and herding are supported.

Jlassi and Naoui (2016) found that only during bull markets and on days with significant trading volume does herding prevail. Moreover, herding had a role in the subprime crisis by inflating the housing bubble and causing excessive market volatility. Evidence of asymmetric herding was observed during periods of low volatility.

An examination of the existing body of work concerning herding behavior in financial markets uncovers an intricate and diverse phenomenon. Kyriazis (2020) and Sahin (2020) both highlight the role of human psychology and irrational behavior in driving herding, with Kyriazis (2020) specifically noting its prevalence in bull markets. Bikhchandani (2000) and Sharma (2000) provide a comprehensive overview of the theoretical and empirical research on herding, emphasizing its potential to destabilize markets and increase financial fragility. These studies collectively underscore the need for further research to better understand and mitigate the impact of herding in financial markets.

Research on herding behavior in financial markets, including the derivative market, has revealed its significant impact on asset price dynamics (Bischi, 2006). This behavior is particularly prevalent during bull periods and high trading volume days, contributing to market volatility and the formation of bubbles (Jlassi, 2015). The presence of herding behavior has also been linked to heavy-tailed distributions in stock price variations (Cont, 1997). Furthermore, it has been found to be more pronounced in high-liquidity stocks, with a notable effect on equity market liquidity (Galariotis, 2016). These studies collectively highlight the influence of herding behavior on market dynamics and the potential implications for derivative markets.

Research on herding behavior in the Indian stock market has yielded mixed results. Poshakwale (2014) and Lao (2011) both found evidence of significant herding behavior, with Poshakwale noting its persistence in both bull and bear markets. However, Lao (2011) also observed that herding behavior was more prevalent during up-swings in market conditions. In contrast, Satish (2018) found no indication of herding behavior among Indian stocks, even during the global financial crisis. These conflicting findings suggest that further research is needed to fully understand the presence and impact of herding behavior in the Indian stock market.

Research Methodology:

Numerous studies have been conducted which prove the presence of herding bias in investor behavior. However, to the best of this researcher's knowledge, the factors that impact the herding bias, specifically in the derivative segment have not yet been undertaken at the time of this study. Therefore, this study aims to find the factors that impact the herding behavior among the retail investors of the Indian Derivative market. The literature reviewed by the author confirms that the majority of the study conducted to date has been based on secondary data. In this study, primary data has been collected for analyzing the herding behavior. For this purpose, a structured questionnaire is prepared based on the scale of Ritika and Kishore (2020). The scale has been adapted keeping in view that the investors are active in the derivative market. This questionnaire was then distributed among the investors using the Purposive Sampling approach and a total of 197 responses were received. Further study has been conducted using these samples.

Data Analysis & Interpretation:

By exploring the structure within the correlation matrix of the variables in the study factor analysis endeavors to condense the data complexity while safeguarding against significant information loss. Researchers often turn to factor analysis when they suspect the presence of underlying latent factors interlinking the initial variables thereby facilitating a clearer labeling of these factors for better comprehension.

Preceding the commencement of factor analysis, it is vital to confirm the presence of correlations within the dataset. Variables exhibiting trivial or non-existent correlations are unsuitable for subsequent factor analysis procedures. The comprehensive evaluation combining the Kaiser-Meyer-Olkin (KMO) and Bartlett's test diligently scrutinizes the dataset for correlation assessment. A noteworthy correlation is established when the KMO value surpasses 0.5 and the significance level of Bartlett's test falls below 0.05. The assessment of variable collinearity, indicating the degree of association between variables, is recommended to exceed the threshold of 0.4. Individual KMO computations may be undertaken for each variable, with a value exceeding 0.5 deemed as acceptable.

With a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) at 0.790, it is evident that the provided data meets the necessary criteria for in-depth factor analysis. This statistical metric gauges the strength of relationships between variables, a pivotal aspect in conducting meaningful data analysis. Proximity to unity highlights substantial adequacy, confirming the optimal framework within the dataset for facilitated factor extraction.

On examination of Bartlett's Test of Sphericity, the approximate Chi-Square value obtained is 1219.789 with 595 degrees of freedom, yielding a significance level (Sig.) of .000. This outcome further reinforces the validation of the dataset for factor analysis. Noteworthy is the indication of a significant Chi-Square, implying substantial variability between variables and confirming their non-random relationship. In other words, the statistical results decisively support the data's suitability for factor analysis, guaranteeing robust and valid interpretations of the underlying data influences.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.790
	Approx. Chi-Square	1219.789

Bartlett's Test of Sphericity	df	595
	Sig.	.000

After determining the data suitability for factor identification, the responses received have been run through the IBM SPSS software to find out the latent factors identified by the study using Exploratory Factor Analysis. Exploratory factor analysis (EFA) is a valuable tool in the social sciences, used for data reduction and exploring scale validity (Finch, 2019). It is particularly important in the development and validation of psychological theories and measurements (Watkins, 2018). EFA involves several methodological decisions, such as sample size, extraction, number of factors, and rotational methods, which should be made thoughtfully and based on evidence (Taherdoost, 2014; Watkins, 2018; Gomez, et al., 2022).

With the use of EFA, we aim to identify the latent factors that influence the herding behavior of the investors in the derivative segment of the market.

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.620	30.343	30.343	10.385	29.672	29.672	4.107	11.734	11.734
2	3.170	9.056	39.399	2.941	8.402	38.073	3.487	9.964	21.698
3	2.594	7.412	46.811	2.344	6.697	44.771	3.476	9.930	31.629
4	2.261	6.460	53.271	2.011	5.744	50.515	2.786	7.959	39.588
5	2.144	6.126	59.397	1.909	5.454	55.970	2.499	7.139	46.727
6	1.797	5.136	64.533	1.543	4.407	60.377	2.216	6.331	53.058
7	1.432	4.092	68.625	1.150	3.286	63.662	1.985	5.671	58.729
8	1.287	3.677	72.302	1.025	2.929	66.591	1.436	4.102	62.831
9	1.238	3.536	75.838	.940	2.686	69.277	1.430	4.087	66.918
10	1.067	3.048	78.887	.811	2.318	71.595	1.319	3.770	70.688
11	1.050	2.999	81.886	.767	2.191	73.786	1.084	3.098	73.786
12	.877	2.505	84.391						
13	.822	2.348	86.740						
14	.652	1.862	88.601						
15	.550	1.570	90.172						
16	.526	1.502	91.673						
17	.421	1.203	92.876						
18	.410	1.171	94.048						

19	.354	1.010	95.058						
20	.281	.802	95.860						
21	.245	.699	96.559						
22	.219	.625	97.184						
23	.201	.575	97.760						
24	.169	.483	98.242						
25	.141	.401	98.644						
26	.125	.357	99.000						
27	.100	.286	99.286						
28	.084	.240	99.527						
29	.043	.124	99.651						
30	.041	.118	99.769						
31	.029	.083	99.851						
32	.022	.063	99.914						
33	.016	.045	99.959						
34	.008	.023	99.982						
35	.006	.018	100.000						
Extraction Method: Principal Axis Factoring.									

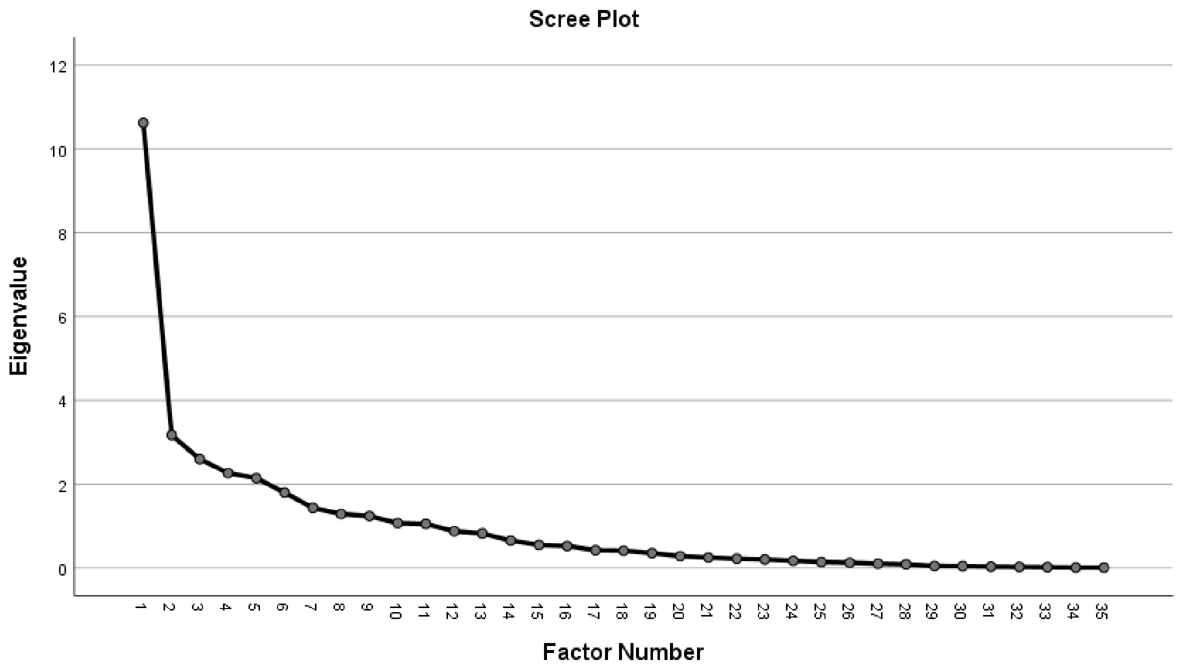
The table above showcases the outcomes of factor analysis conducted through Principal Axis Factoring, outlining the variance accounted for by individual factors extracted from the dataset. Below is a brief explanation of these results.

The first eigenvalue denotes the variance explained by each factor before any transformation. Initially, Factor 1 records the highest variance, starting at an eigenvalue of 10.620, which gradually diminishes as we move to the following factors. This initial eigenvalue signifies the complete variance associated with each specific factor.

The Extraction Sums of Squared Loadings reveal the proportion of variance accounted for by each factor following extraction but before rotation. Factor 1 preserves a significant proportion of variance at 29.672%, with Factor 2 at 8.402%, and subsequent factors following suit. Collectively, the initial three factors elucidate 44.771% of the total variance, indicating their paramount importance within the dataset.

Rotation Sums of Squared Loadings illustrate the proportion of variance explained by individual factors following the rotation process, which aims to streamline the factor arrangement and improve clarity. Post-rotation, it is noteworthy that Factors 1, 2, and 3 collectively maintain a substantial share of 31.629% in explaining the variance.

The outcomes suggest that the primary factors account for most of the variation in the data, affirming their significance in summarizing the connections between the variables examined. This in-depth methodology aids in comprehending the factorial arrangement and interpreting the dataset's intricacy efficiently. Visualization of the above data is done in the scree plot below.



Rotated Component Matrix[a]

	Component										
	1	2	3	4	5	6	7	8	9	10	11
V14											.744
V15			.820								
V16			.511								
V17		.709									
V18		.647	.520								
V19											
V20				.555							
V21					.878						
V22									.624		
V23		.780									
V24	.571										
V25		.837									
V26		.756									
V27				.579							
V28						.822					
V29						.898					
V30									.824		
V31					.677						
V32										.863	
V33								.577			
V34				.784							

V35				.829							
V39							.789				
V40	.823										
V41								.881			
V42	.575										
V43											
V44	.811										
V45			.732								
V46			.768								
V47	.698										
V48							.586				
V49							.590				
V50					.628						
V51	.616										

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 15 iterations.

The Rotated Component Matrix offers a valuable analysis of the inherent structure in the data by pinpointing the key components using Principal Component Analysis (PCA) coupled with Varimax rotation. This matrix illustrates the factor loadings, indicating the correlations between the variables and the derived factors, providing a more precise understanding of the data's complexity. Varimax rotation is utilized to streamline the factor arrangement, facilitating the identification of significant patterns and connections among the variables.

The table above shows the factor loadings of various items. All loadings below 0.5 have been suppressed, following the studies of Costello and Osborne (2005) indicating each latent variable should be capable of explaining a minimum of 50% of the construct. Thus, only those variables obtaining a loading above 0.5 have been taken for our study. All the variables have loaded on a total of 11 factors which have then been rotated using varimax rotation. The rotated component matrix helps in simplifying and clarifying the structure of the data by maximizing the loadings of each variable on one component while minimizing the loadings on others. This orthogonal rotation method ensures that the components remain uncorrelated, aiding in the interpretation of results.

These factors highlight different dimensions captured by the variables, each representing unique constructs within the data. The high loadings on certain variables indicate their strong association with specific factors, while moderate and negative loadings add depth to the interpretation. This detailed breakdown helps identify key variables and their contributions to different dimensions, helping in setting parameters for further study.

Upon closer examination, two of these eleven factors were found to be represented by only one variable each, with factor loadings of 0.866 and 0.744, respectively. Specifically**,** Factor 10 was uniquely defined by variable V14 with a high loading of 0.744, and Factor 11 was represented primarily by variable V30, with a high loading of 0.866. While these loadings are substantial, indicating a strong correlation between the variables and their respective factors, they are insufficient to comprehensively explain the underlying constructs.

A robust factor analysis ideally requires each factor to be represented by multiple variables to ensure that the extracted factors are reliable and interpretable. This necessity is underscored by the literature on factor analysis, particularly the works of Fabrigar et al. (1999) and Costello and Osborne (2005). These scholars argue that a minimum of three item loadings per factor is essential for a meaningful and stable factor solution. The rationale behind this recommendation lies in the increased reliability and validity of factors when they are supported by multiple indicators. Single-item factors are prone to idiosyncratic variance, which can distort the overall analysis and lead to misleading conclusions.

Given this theoretical underpinning, the two factors with only one variable each were deemed insufficient for comprehensive explanation and were subsequently excluded from further analysis. This decision aligns with best practices in factor analysis, ensuring that the remaining factors are more robust and interpretable.

The remaining nine factors, each supported by multiple variables, provide a more reliable and nuanced understanding of the dataset. Therefore, only these 9 factors have been taken for further study. The factors each exhibited common factors of the variables. Based on this, the factors have been named as follows:

Factor 1 is Public Information. This includes all information received from newspapers, magazines, and special issues, among others.

Factor 2 captures the fear and pressure felt by the investors due to the investment results and advice of their peers. Hence, this factor is named as Peer Influence.

Factor 3 talks about the influence that social and personal groups have on investors. This factor is called Social Group and includes friends, family, and other forms of social groups that an investor is exposed to.

Factor 4 considers the impact of others earning profits from the same or similar trades. This creates psychological pressure for individuals to take up trades that would in turn result in profits for them as well. Thus, it has been named as Fear of Missing Out.

Factor 5 considers the influence of the personal knowledge levels of these investors and the trust they put in others. The more investors rely on their knowledge, the less likely they are to herd. On the other hand, if the investor faces uncertainty about their knowledge levels, they are more likely to herd. On the other hand, the advices are also followed based on the level of trust in the individual giving suggestions.

Factor 6 captures the influence of prior experience of the investors in the market. It was found that the investors are more likely to herd when they have either suffered losses in the past when the trades were taken based on their own analysis or have earned profits when they followed others. Thus, this factor is called Prior Experience.

Factor 7 is judging the confidence of investors in the market. Investor who is unsure of their decisions and cannot believe in their analysis are more prone to herd mentality. Hence, underconfidence also becomes another reason that could lead to significant influence of others in decision making; this factor is named as Under-confidence.

Factor 8 is named as Financial Experts and Brokers, due to the influence these non-acquaintances have on an investor's decision. The study reveals that investors do make trades based on the advice received from their brokers and other people they consider better traders than themselves.

Factor 9 is named as Social Media Influence. The study reveals that investors do follow famous financial gurus and highly successful investors on various social media, even to the extent of adopting their advice and replicating their suggested portfolios in their social media posts and feeds.

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.897	.882	51

After conducting an Exploratory Factor Analysis (EFA), we proceeded to assess the internal consistency of the identified factors using Cronbach's Alpha. The reliability analysis yielded a Cronbach's Alpha value of 0.897 and a Cronbach's Alpha based on standardized items of 0.882 for the 51-item scale. These results indicate a high level of internal consistency among the items, suggesting that they reliably measure the underlying construct. In the context of psychometric evaluations, a Cronbach's Alpha value above 0.70 is generally considered acceptable, with values above 0.80 being good, and those above 0.90 deemed excellent. Therefore, the obtained values of 0.897 and 0.882 signify that the scale is exceptionally reliable. The high reliability statistics reinforce the validity of the items in capturing the intended construct, providing confidence that the scale will yield consistent and dependable results in further research applications. Despite the high Cronbach's Alpha, it is important to ensure that each item contributes uniquely and meaningfully to the scale, avoiding redundancy and maintaining the robustness of the measurement tool.

Summary Item Statistics							
	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.157	-.392	.833	1.225	-2.126	.059	514

Following the reliability analysis, we examined the inter-item correlations to further evaluate the internal consistency and redundancy of the items. The summary item statistics provide a detailed overview of the inter-item correlations within the 51-item scale. The mean inter-item correlation is 0.157, indicating a moderate average relationship between items. This value suggests that, on average, the items share a reasonable degree of common variance, supporting the coherence of the scale.

The minimum inter-item correlation is -0.392, while the maximum is 0.833, resulting in a range of 1.225. The presence of negative correlations indicates that some items may be inversely related, which could highlight areas where the scale might include items measuring slightly different aspects of the construct or possibly opposing constructs. The maximum inter-item correlation of 0.833 suggests strong relationships among certain items, which might imply some redundancy or very closely related content.

The maximum/minimum ratio of -2.126, which is negative due to the presence of negative correlations, further emphasizes the variation in relationships between items. This broad range and ratio can be a sign of a diverse set of items, which might be capturing different facets of the underlying construct.

The variance of the inter-item correlations is 0.059, indicating some spread in the degree of relatedness among items. A higher variance in inter-item correlations could point to a heterogeneous set of items, capturing a broader spectrum of the construct.

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig
Between People		596.750	73	8.175		
Within People	Between Items	1269.470	39	32.551	38.627	.000
	Residual	2399.155	2847	.843		
	Total	3668.625	2886	1.271		
Total		4265.375	2959	1.441		
Grand Mean = 2.86						

The Analysis of Variance (ANOVA) results provide critical insights into the variability within the dataset and the significance of differences observed. The table presents the sum of squares, degrees of freedom, mean squares, F-value, and significance level for both between-person and within-person analyses.

Firstly, the between-people analysis reveals a sum of squares of 596.750 with 73 degrees of freedom. The mean square, calculated by dividing the sum of squares by the degrees of freedom, is 8.175. This represents the average variance between the individuals participating in the study. High variability between people suggests substantial differences in responses across participants, which could be due to individual differences in perceptions, experiences, or interpretations of the items.

The within-people analysis is further divided into between-items and residual components. The between-items analysis examines the variability across the different items used in the study. With a sum of squares of 1269.470 and 39 degrees of freedom, the mean square is 32.551. The F-value for this component is 38.627, with a significance level (Sig) of .000, indicating that the differences observed between items are statistically significant. This implies that the items in the scale measure distinct aspects of the construct, contributing significantly to the total variance.

The residual sum of squares within people, which represents the unexplained variance or error, is 2399.155 with 2847 degrees of freedom, resulting in a mean square of 0.843. The residual component captures the variability not explained by the items or participants, reflecting random error or other unmeasured factors influencing the responses.

The total sum of squares within people is the sum of the between-items and residual components, totaling 3668.625 with 2886 degrees of freedom and a mean square of 1.271. This indicates the overall variance within individual responses across different items.

Combining the between-people and within-people variances gives the total sum of squares of 4265.375 with 2959 degrees of freedom and an overall mean square of 1.441. This value represents the total variance in the dataset, encompassing both individual differences and item-specific variability. The grand mean, or the overall average score across all items and participants, is 2.86. This provides a baseline measure of the central tendency of responses in the dataset.

The ANOVA results highlight significant variability both between participants and between items, with statistically significant differences observed among the items. The high F-value and low significance level for the between-items component confirm that the items are effectively capturing different dimensions of the construct. Meanwhile, the substantial between-people variability underscores the importance of considering individual differences in interpreting the results. The grand mean offers a useful summary measure of the central tendency across the entire dataset. Together, these findings support the robustness of the scale and its ability to differentiate among various facets of the construct being studied.

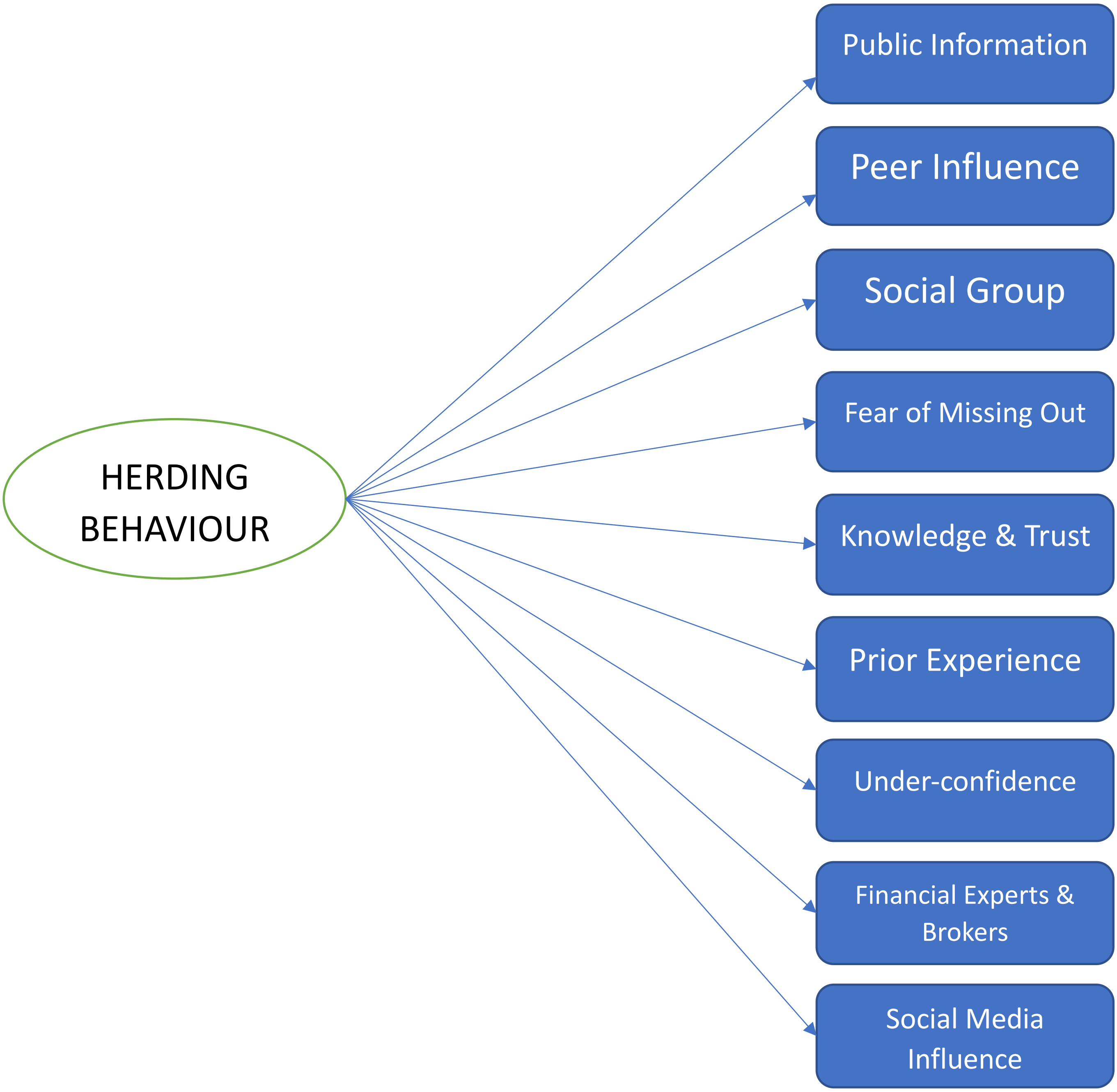


Figure 1: External Factors identified

Theoretical and Managerial Implication:

This study uses an Exploratory Factor Analysis (EFA) to identify and validate nine distinct components, making a substantial contribution to theoretical frameworks that explain seemingly irrational yet predictable patterns in investors' decision-making practices.

Some of the factors like fear of missing out (FOMO), social influence, and under-confidence shed light on how the differences arising from interactions produce herding behavior in derivative markets. The theoretical development that sharpens insight into the formation of psychological and social dynamics determining investor behavior is an extension of theory within behavioral finance. The factors identified have nuances about the nature of how individual psychological variables intersect with market conditions in influencing collective behaviors, hence establishing a framework based on empirical data from which further study can evolve to include all additional factors, confirm hypotheses under different market conditions, and further hone theoretical constructs within behavioral finance. This continuous theoretical development is crucial in creating further knowledge that must inform both academic research and practical application within financial markets.

Investor education programs can be improved thereby providing investors with a better understanding of herd behavior risks and enable independent choice-making.

More importantly, financial institutions can improve their risk management abilities by incorporating knowledge of those factors. In that manner, by monitoring improved market sentiment, identified possible herd behavior early on, the adverse impact on market stability can be mitigated. Improved risk controls, which are also tailored to address such factors that are identified will further enhance the resilience to market volatility and lead to more stable financial results.

These findings will not only be useful to risk management but also guide product design and communication strategies. From having a more informed understanding of investor behavior, firms will be able to line up their offerings with the needs of different investors while keeping a lid on the possibility of herd-driven market fluctuations.

Lastly, regulatory bodies can do much through improvement of regulations in regard to issues that encourage herding. The actions that should be undertaken include regulation on enhancement of transparency of markets, transparency of the whole investment environment, and discouragement of further reckless herd-inducing practices. Providing proper regulation that fully takes into account behavioral insights will help in creating a more stable financial market environment, which will benefit investors and, in general, the economy as well.

Limitations of the Study:

The study makes use of primary data to identify the factors that have an impact on the herding behavior exhibited by the retail investors of the Indian derivative market. However, the study is wrought with certain limitations despite the best efforts of the researcher. These are enumerated below:

- As the study is based on primary data, there is respondent bias influencing the data. The respondents may be prejudiced while recording the data.
- The time frame of the study is 6 months. Studies prove that psychological factors tend to change with change in time factors (Salthouse et al, 2006)
- The data is also constrained to the urban population and does not consider the investors primarily residing in the rural areas of the country.

Herding behavior is a combination of complex psychological and social factors. Some of the aspects like information cascade have not been considered. This implies that the psychological changes due to political disturbances, and major news disbursement have not been studied here

Conclusion:

The study conducted was intended to find the factors that have an impact on the herding behavior of investors participating in the Indian derivative market. The data reveals that nine factors impact the herding behavior exhibited by the investors. These factors are correlated with each other and individually as well as collectively influence the way an investor behaves. The impact of peers, family, friends, knowledge and trust, financial experts and brokers, under-confidence, public information, fear of missing out, prior experience, and social media news have an impact on investor herding behavior. This study is significant for retail investors as well as agents, brokers, and institutions in identifying and predicting investor behavior. The herd mentality has been responsible for the market movement as the studies prove. Studies have also supported the fact that investors when following a popular opinion in investment decision-making making have the power to influence the market movement. This study will help the intermediaries and corporates in using the identifying factors in policy-making as well as making investment decisions. It will also help retail investors mitigate the impact of herding behavior by considering the influence of individual factors on their behavior. Further research can be in analyzing the difference in factors impacting herd behavior in various market segments. Also, this study will help in analyzing the impact of other behavioral biases on these factors. Researchers may also look into the geographical impact on the factors impacting the herding behavior of investors.

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