ORIGINAL ARTICLE

OPEN ACCESS

When Market Misbehaves: An Irrational Version of the Asset Pricing Model in the Emerging Market of Pakistan

Zain-ul-Abidin [1], Muhammad Zia-ur-Rehman [2], Khalid Latif [3]

Author's Affiliation:

[1,2]Faisalabad Business School, National Textile University, Faisalabad, Pakistan
[3]Associate Professor, College of Commerce, Government College University, Faisalabad

Article History:

Submitted: June 13, 2025
Revised: September 26, 2025
Accepted: September 28, 2025
Published online: September 30, 2025

Corresponding author(s):

Zain-ul-Abidin
Email:
zainulabidinfida@hotmail.com

Co-author(s)Email:

Muhammad Zia-ur-Rehman
mzrehman@ntu.edu.pk

Khalid Latif
khalidlatif@gcuf.edu.pk

ABSTRACT

The traditional asset pricing model assumes investors' rationality, yet the emerging markets misbehave, and our most fundamental pricing models simply fail to defend their myth.

Purpose—This study aims to develop the Behaviorally Extended Capital Asset Pricing Model (BECAPM), an irrational version of the CAPM by incorporating six behavioral variables in the traditional single-factor model to check predictability improvement of returns in the context of emerging capital markets like the Pakistan stock exchange.

Study Design/methodology/approach—Accumulating the daily data of 100 listed companies of the KSE-100 Index from 2005 to 2024 from PSX official website, SBP data center, and investing.com, behavioral variables have been constructed using price dispersions, cumulative abnormal returns, Cross-Sectional Absolute Deviation (CSAD), principal component, and dividend announcements as highlighted by the existing literature. Seven nested regression models with Newey-West robust standard errors were estimated and compared for prediction accuracy.

Findings—The fully extended BECAPM demonstrates a 48% improvement in explanatory power over single-factor CAPM. Though the primacy of systematic risk remains dominant, herding exhibits the strongest negative impact ($\beta = -1.052$), and dividend preference emerges as the most significant positive factor ($\beta = 0.387$). Model selection criteria unanimously support behavioral extensions. Structural break analysis reveals amplified behavioral effects during crisis periods (2008 financial crisis, 2020 pandemic).

Practical Implications—This study would be helpful to the portfolio managers in better decision making for investments, the regulators in devising a better monitoring system for speculative trading, and the academics to enhance financial literacy programs that target the reduction in cognitive bias to enhance market efficiency and snub mispricing.

Limitations—The construction of behavioral factors relies on market-based proxies rather than direct psychological measures. Analysis of single market limits generalization.

Originality/value—It is the first study in our knowledge to incorporate multiple psychological factors into a unified pricing model and provide empirical validation of behavioral risk factors simultaneously.

Keywords: Behavioral-CAPM, Capital Asset Pricing Model (CAPM), Emerging Markets, Herding, Investor Psychology, Overconfidence, Over-reaction, Pakistan Stock Exchange (PSX), Sentiment, Under-reaction.

JEL Classification Codes: G12, G41, C58, D91

1 | INTRODUCTION

1.1 | Background and Research Motivation

The modern financial theory assumes that investors are rational people and markets are effective in information incorporation. Behavioral finance demonstrates, however, that this assumption is too narrow because psychological biases, emotions, and social factors often become the driving forces of price changes. This can be well exemplified by the 2008 financial crisis, whereby fear, uncertainty, and herd behavior drove prices beyond fundamentals, and this proves that human behavior is immensely powerful in asset pricing (Hirshleifer, 2020).

High contributions from retail investors, inadequate as well as uneven access to information, and low financial literacy create conditions in which sentiment and cognitive biases exert strong influence over price movements (Nguyen & Nguyen, 2025; Zaiane, 2013). As an emerging market, the Pakistan Stock Exchange also reflects such behaviors as frequent impulsive cycles, speculative price swings, and herd patterns (Abideen et al., 2023; Jabeen et al., 2023; Perveen et al., 2024). Though behavioral effects on financial choices are also gaining growing recognition, they are not well represented in the formal asset-pricing models. The bulk of the previous research is focused on individual biases separately, e.g., the studies of Yuan (2015), which constructed sentiment-based factors showing investor sentiment's predictability of returns. However, their framework focuses on a single behavioral dimension (sentiment) rather than multiple interacting biases. Similarly, Hens and Naebi (2022) proposed theoretical frameworks for integrating behavioral factors into CAPM but provided limited empirical validation, particularly in emerging markets, and Gokhale and Mittal (2024) examined herding and overconfidence effects on Indian equity returns but analyzed factors separately rather than jointly estimating a comprehensive behavioral model. Thus, fails to fill the gap between psychological and conventional risk-established models. The Sharpe-Lintner CAPM, which relates the expected returns to market beta, remains a principal valuation model, but has not worked consistently in practice, indicating the necessity of models that include various factors into a single pricing framework. Several well-known anomalies, including size effects (Banz, 1981), value premiums (Fama & French, 1995), and post-earnings announcement drift (Bernard & Thomas, 1989), show that market beta alone cannot explain observed return patterns. In the opinion of Yuan (2015), even multi-factor models like (Fama & French, 2015; Fama & French, 2018) leave important gaps unsolved. These findings indicate that investor behavior is not merely noise but a meaningful source that should be formally incorporated into asset-pricing frameworks.

1.2 | Research Problem

CAPM assumes that investors are rational and share similar expectations; this assumption does not fit well in emerging markets, where behavioral biases are widespread. This creates a clear gap in the literature, as existing research rarely brings multiple psychological factors together within a single empirical framework. Despite a growing literature, three problems still exist. First, most studies examine individual biases separately rather than assessing their combined impact on asset prices, as evident from the studies of (Bajo et al., 2023; Gokhale & Mittal, 2024; Jabeen et al., 2023; Rahman et al., 2022; Zia Ur Rehman et al., 2017). Second, much of the behavioral pricing literature focuses on developed markets, even though such biases are likely to be more pronounced in developing markets, as in the studies of (Dirir, 2022; Khan, 2024; Nguyen & Parsons, 2022; Zia Ur Rehman et al., 2017). Third, several studies consider behavioral influences only indirectly, treating them as anomalies rather than formal risk components that should be integrated into asset pricing models, as evident from (Almansour et al., 2023; Fama & French, 2015; Zhang, 2025).

1.3 | Research Questions

This study addresses these gaps by investigating three interrelated research questions:

RQ1: Do behavioral risk factors provide incremental explanatory power beyond traditional market beta in explaining cross-sectional return variation?

RQ2: Does a behaviorally extended CAPM (BECAPM) demonstrate superior explanatory and predictive performance compared to the traditional single-factor CAPM?

1.4 | Research Objectives

1. To measure six behavioral betas using market-observable proxies in light of previous literature.
2. To add and empirically assess whether behavioral factors improve the explanatory power of single-factor CAPM in the emerging market (e.g., Pakistan Stock Exchange)
3. To compare the explanatory and predictive power of the BECAPM with traditional single-factor CAPM.

1.5 | Rationale for Single Factor CAPM

Since it is the first study in its nature to incorporate behavioral factors to asset pricing stream we have started with the simplest form of Asset Pricing Models furthermore, the simplicity of the model eases behavioral effects (FU, 2025); the model, despite its empirical limitations, provides a widely accepted base for asset evaluation (Dirir, 2022); and the objective of demonstrating behavioral effects as risk factors instead of substitutes to market beta could easily be achieved (Hens & Naebi, 2022). The application of the single-factor CAPM could also explain the incremental value of behavioral dimensions and provide a basis for future multi-factor extensions (ul Abdin et al., 2017), which will be our next destination.

Based on the Prospect Theory and Cumulative Prospect Theory (Kahneman & Tversky, 1984, 2013; Tversky & Kahneman, 1992), the research describes how reference dependence, loss aversion, and distortion of probabilities create momentum, overreaction, and speculative trade in sentiment markets such as the PSX, which fills a significant gap in the emerging-market asset-pricing literature.

1.6 | Research Contributions

There is a threefold contribution of this research framework in behavioral asset pricing literature. Firstly, the development of a comprehensive multi-dimensional behavioral asset pricing model designed for emerging markets. Secondly, an empirically tested demonstration of behavioral factors as risk factors rather than exploitable anomalies. Finally, a behaviorally extended asset pricing model for risk management, portfolio construction, and regulatory surveillance in emerging market contexts.

2 | LITERATURE REVIEW

2.1 | Theoretical Evolution of Asset Pricing

The modern asset pricing theory could be traced back to Markowitz (1952) Modern Portfolio Theory (MPT), which introduced the concept that investors could balance risk and return by strategically diversifying their portfolios. By optimizing the trade-off between expected returns and risk, he formed the idea of the efficient frontier, guiding investors toward optimal portfolio construction. Sharpe (1964) extended the MPT by framing the Capital Asset Pricing Model (CAPM) and connecting the expected returns to a single measure known as systematic risk or beta(β). (Lintner, 1975) reinforced CAPM as a central framework for asset valuation.

2.2 | Efficient Market Hypothesis

Fama (1970) provided theoretical support for CAPM through the Efficient Market Hypothesis (EMH). Based on the rational investor theorem, they argued that financial markets incorporate all available information into prices and therefore, consistent abnormal returns were unattainable. This hypothesis, based on three assumptions, i.e., investor rationality, independent deviations, and arbitrage forces that eliminate any remaining mispricing, divided the markets into three forms of efficiencies, i.e., weak efficient markets, semi-strong efficient markets, and strong efficient markets.

2.3 | Challenges to Asset Pricing and Multi-Factor Models

Despite its wide acceptance, CAPM has constantly faced empirical challenges. Banz (1981) highlighted the size effect by showing that small-cap stocks tend to outperform the model with beta alone. Fama and French (1995) discovered the value premium, i.e., firms with high book-to-market ratios gained excess returns regularly. Bernard and Thomas (1989) observed post-earnings announcement drift, i.e., stock prices tend to move in similar directions even long after the announcement.

To address these anomalies, Fama and French (1993) proposed a three-factor model that incorporated size (SMB) and value (HML) in addition to market beta. Later, they extended this model to five factors Fama and French (2015) by adding profitability and investment patterns. Hou et al. (2015) developed a q-factor model by incorporating investment and profitability factors. Still, these sophisticated multi-factor models left significant anomalies, indicating that there remain some unaccounted factors beyond the firm fundamentals (Yuan, 2015).

2.4 | Emergence of Behavioral Finance

The limitations of rational models paved a path for investor psychology into asset pricing, and thus, behavioral finance emerged as a field that incorporated psychological factors into financial econometrics to explain consistent deviations from rational expectations. De Bondt and Thaler (1985) provided pivotal evidence of overreaction by showing that stock prices often reverse after extreme past performances. Jegadeesh and Titman (1993) documented momentum effects, showing that winning stocks tend to continue rising, which contradicts the random walk hypothesis. The 2008 global financial crisis further highlighted the impact of investor psychology, where fear, panic, and herd behavior pushed markets far from the fundamental values (Hirshleifer, 2020). Barberis et al. (1998) explained over- and under-reaction due to investor heuristics known as representativeness and conservatism. Daniel et al. (1998) proved that overconfidence and self-attribution steer excess volatility and momentum in asset prices. These studies evidently prove that investors process information through cognitive and emotional filters. Thus, creating a continual variation from fundamental asset pricing through excessive trading, following the actions of others, prefer "certain income" over "uncertain capital gains" (Baker & Wurgler, 2007; Shefrin & Statman, 2000).

2.5 | Key Behavioral Biases and Market Anomalies

2.5.1. Overconfidence

When investors tend to overvalue their knowledge and underrate potential risks, it often leads to excessive trading and mispricing Odean (1998). Empirical studies proved that overconfident investors trade aggressively during bull markets (Aljifri, 2023; Bouteska et al., 2023).

2.5.2. Over-Reaction and Under-Reaction

De Bondt and Thaler (1985) demonstrated that news often triggers a reaction in investors, generating a momentum in prices in the direction of the news (Hong & Stein, 1999; Jegadeesh & Titman, 1993). Barberis and Thaler (2003) explained these patterns by representativeness heuristics, which cause investors to overweight recent information, and conservatism, which leads to underweighting of information (Kumar, 2022).

2.5.3. Herding Behavior

Herding arises when investors imitate collective actions instead of trusting their own private information. It often intensifies market bubbles or crashes. Christie and Huang (1995)and Chiang and Zheng (2010) devised methods to detect herding by using cross-sectional return deviations. There have been empirical examples (Hassan & Jamil, 2021; Jabeen et al., 2023; Perveen et al., 2024) during stressed periods of the market, where return dispersion narrowed due to prevailing price trends.

2.5.4. Investor Sentiment

Investor sentiment or prevailing market mood could manipulate prices independently of fundamental values (Baker & Wurgler, 2007). Sentiment plays a particularly strong role due to lower transparency and higher rumors. Studies like Rahman et al. (2022) and Zia Ur Rehman et al. (2017) showed that trading-volume-based sentiment indices could predict stock returns beyond traditional CAPM factors, thus emphasizing their importance as a systematic risk factor.

2.5.5. Bird-in-Hand Fallacy

Miller and Modigliani (1961) argument about dividends' irrelevance regarding the influence of firm value, investors prefer certain dividend income instead of uncertain capital gains. Behavioral finance explains this preference by the concept of mental accounting, loss aversion, and ambiguity avoidance (Barberis & Thaler, 2003; Shefrin & Statman, 1984). Empirical studies like (Desmettre et al., 2018; Guo et al., 2023; Kim et al., 2024; Nababan et al., 2025; Yoo & Ahn, 2025) indicated that dividend-paying stocks are often overvalued because their perceived risk is higher due to asymmetric information.

2.6 | Behavioral Finance in Emerging Markets

Behavioral influences amplify in emerging markets due to structural characteristics that intensify psychological biases:

- Information Asymmetry. Limited analyst coverage, sparse financial reporting, and weak disclosure regulations create information vacuums filled by rumors and sentiment rather than fundamental analysis (Chen & Liu, 2023).
- Weak Institutional Infrastructure. Limited short-selling, underdeveloped derivatives markets, and capital controls restrict arbitrage mechanisms that might correct mispricing (Chiang & Zheng, 2010).

- Macroeconomic Volatility. Frequent currency crises, political instability, and policy uncertainty heighten loss aversion and amplify herding as investors seek safety in consensus (Nguyen & Nguyen, 2025).

2.6.1. Empirical evidence confirms these patterns in emerging markets

Multiple studies document significant herding behavior in Pakistan's equity market, particularly during crisis periods. Jabeen et al. (2023) find strong herding during the COVID-19 pandemic.Perveen et al. (2024) demonstrate that herding intensifies during both market crashes and rallies. Hassan & Jamil (2021) show herding is more pronounced in small-cap stocks with limited analyst coverage, consistent with information-based herding explanations. Zia Ur Rehman et al. (2017) construct a composite sentiment index for Pakistan using turnover, money flow, and technical indicators, finding that sentiment significantly predicts returns beyond CAPM factors. Rahman et al. (2022) demonstrate that sentiment effects are strongest for small, young, and volatile stocks, whose values depend heavily on subjective growth expectations. Abideen et al. (2023) document excessive trading during bull markets in Pakistan, consistent with overconfidence.Bouteska et al. (2023) find that overconfidence-driven trading increases around political events, when investors overestimate their ability to predict policy outcomes.

Momentum and Reversal: Khan (2024) demonstrates significant momentum profits in Pakistan's equity market over 3 to 12-month horizons, followed by long-term reversal patterns consistent with underreaction to news, followed by overreaction to accumulated evidence. Wang et al. (2024) find similar patterns across South Asian markets.

Dividend Preferences: Limited research directly addresses dividend preferences in the Pakistani context, though Raza et al. (2018) document substantial dividend clienteles with dividend-paying stocks commanding valuation premiums beyond tax or liquidity explanations. KORPES (2023) and Yoo and Ahn (2025) find similar dividend preference patterns in other emerging markets, attributed to loss aversion and uncertainty avoidance.

2.6.2. Integration of Behavioral Factors into Asset Pricing Models

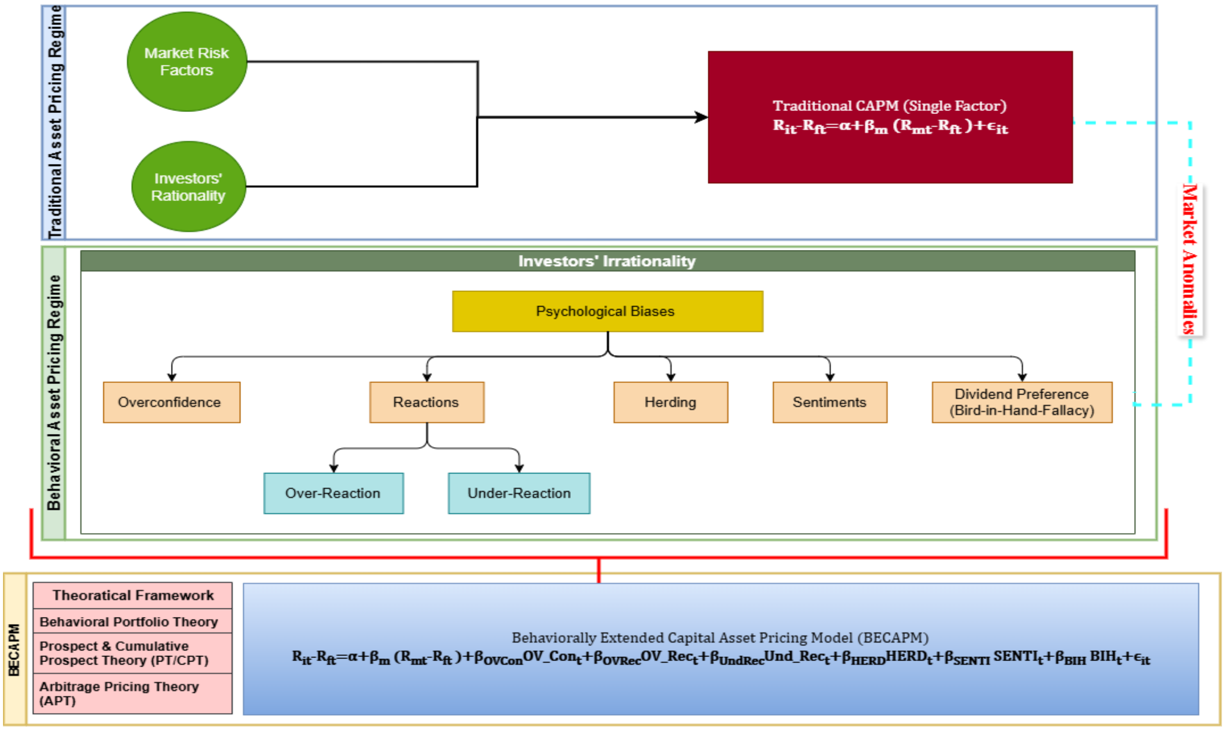
Despite extensive documentation of behavioral biases, few studies formally integrate multiple psychological factors into unified asset pricing frameworks:

Single-Bias Focus: Despite growing literature of behavioral finance, recent studies focus on individual biases, e.g., overconfidence (Aljifri, 2023), herding (Jabeen et al., 2023), and sentiment (Rahman et al., 2022) in isolation, blocking out potential connections of these biases into a comprehensive behavioral pricing model.

Anomaly vs. Risk Factor Treatment: Existing literature primarily treats behavioral patterns as exploitable anomalies instead of considering them as systematic risk factors (Almansour et al., 2023).

Figure 1

Conceptual Framework for Behaviorally Extended Capital Asset Pricing Model (BECAPM)



(Authors' self-contribution)

Figure 1 depicts the conceptual framework of expanding the CAPM baseline by six behavioral factors to full BECAPM in light of foundations in Behavioral Portfolio Theory, Prospect Theory/Cumulative Prospect Theory, and Arbitrage Pricing Theory.

3 | METHODOLOGY & DESIGN

3.1 | Data and Sample

This study employs a quantitative approach using secondary market data to test whether behavioral factors enhance traditional single-factor CAPM's explanatory power in Pakistan's equity market. We construct behavioral risk factors through established proxies from behavioral finance literature, estimate nested regression models using Newey-West robust standard errors to address autocorrelation and heteroskedasticity, and compare model performance via information criteria and out-of-sample validation.

3.2 | Data Source

We employ multiple data sources to ensure comprehensiveness and cross-validation:

- **Closing Prices:** Daily closing prices, trading volumes, and shares outstanding for all KSE-100 Index constituents sourced from Pakistan Stock Exchange official databases (PSX Data Portal: https://dps.psx.com.pk). Data collection period: January 1, 2005, to December 31, 2024.
- **Risk-free Rate:** Daily risk-free rate proxied by 3-month Pakistan Treasury Bills (T-Bills) obtained from the State Bank of Pakistan Economic Data Repository. We convert the annualized 3-month T-Bill rate to a daily equivalent using:

- $$\text{Daily Rf} = \left[(1 + \text{Annual Rate})^{\frac{1}{365}}\right] - 1$$

- This ensures temporal consistency with daily return calculations. We interpolate T-Bill rates linearly between auction dates (typically weekly) to obtain a daily series.
- **Market Index:** KSE-100 Index daily total return series (including dividends) sourced from PSX and validated against Bloomberg and Investing.com. Total return index calculation ensures dividend payments are properly reflected in market returns.
- **Dividends Data:** Dividend announcements have been obtained from the PSX corporate announcements database.

3.3 | Sample Selection

100 stocks selected from the KSE-100 Index represent approximately 85% of the PSX market capitalization. To ensure broad market coverage while maintaining data quality, the study adopted the following selection criteria:

- Continuous listing throughout 2005-2024 (survivorship bias acknowledged but necessary for a consistent panel)
- Minimum 70% non-zero trading days (liquidity filter)
- Complete corporate action data available

3.4 | Sample Period Rationale

The period of 2005-2024 captures multiple market cycles, e.g., the 2008 global financial crisis, 2010-2014 political transitions, and 2020-2021 COVID-19 pandemic, supporting robust behavioral pattern identification across diverse market conditions.

3.5 | Variable Construction and Measurement

Dependent Variable: Portfolio Excess Returns

The portfolio returns have been calculated as follows:

$$\mathrm{R_{p,t}} = \frac{1}{\mathrm{N_p}}\sum_{\mathrm{i=1}}^{\mathrm{N_p}} \mathrm{R_{i,t}}$$

where N_p = Number of stocks per portfolio.

The dependent variable is portfolio excess returns, calculated as:

$$\mathrm{ER_{p,t}} = \mathrm{R_{pt}} - \mathrm{R_{ft}} \qquad \text{EQ } \textbf{Error! No text of specified style in document.}.1$$

Where:

- R_{pt} is the return of portfolio p at time t, calculated by sorting the stocks into five quintile portfolios based on prior-year market beta (systematic risk).
- R_{ft} = Risk-free rate is proxied by the daily adjusted 3-month Treasury Bill rate from the State Bank of Pakistan.

Independent Variables: Behavioral factors calculated through market data-driven proxies

The behavioral factors are calculated using market data-driven proxies consistent with empirical behavioral asset-pricing literature (Baker & Wurgler, 2006; Guo et al., 2023; Jabeen et al., 2023; Rahman et al., 2022; Zia Ur Rehman et al., 2017).

Table 1

Variables, Proxies, Justifications, and Key References

Variable	Symbol	Proxy Description	Justification	Key References
Market Return	R_m	PSX-KSE100 log returns	CAPM baseline	(Sharpe, 1964)
Risk-Free Rate	R_f	Daily adjusted 91-day T-bill	Standard risk benchmark	(Fama & French, 2015, 2018)
Dividend Preference (BIH)	β_{BIH}	Excess return premium of dividend vs. non-dividend portfolios	Reflects behavioral preference for certain cash flows	(Korpes, 2023; Raza et al., 2018; Yoo & Ahn, 2025)
Herding	β_{HERD}	Dispersion vs. market return (CSAD deviation)	Captures crowd-following	(Christie & Huang, 1995; Jabeen et al., 2023; Javed et al., 2013)
Sentiment	β_{SENTI}	PCA-based sentiment index of four proxies	Reflects optimism/pessimism	(Baker & Wurgler, 2007; Rahman et al., 2022; Zia Ur Rehman et al., 2017)
Overconfidence	β_{OVCon}	Excess turnover relative to the historical mean	Investors overestimate private info	(Aljifri, 2023; Boujedra & Ismaliia, 2019; Bouteska et al., 2023)
Overreaction	β_{OVRec}	Lagged abnormal returns	Excess reaction to news	(Barberis et al., 2018; Barberis & Thaler, 2003; Bondt & Thaler, 1985; Kapil, 2022)
Underreaction	β_{UndRec}	Momentum factor	Delay in price adjustment	(Daniel et al., 1998; Jegadeesh & Titman, 1993)

3.6 | Overconfidence (Ov_Con)

It is measured to incorporate trade intensity:

$$\mathrm{Ov}_{\mathrm{Con}_t} = \alpha_1 \cdot \mathrm{ExcessTurnover}_t + \alpha_2 \cdot \mathrm{ReturnDispersion}_t$$

EQ **Error! No text of specified style in document.**.2

Where:

- Turnover = $\frac{Volume_t}{Shares\ Outstanding_t}$
- $ExcessTurnover_t = Turnover_t - Turnover_{t-1}$
- $ReturnDispersion_t = \sigma_{cross-sectional}(R_{i,t})$

Overconfident investors generate excess trading volumes because of their exaggerated private information and beliefs; at the same time, they create return dispersion via heterogeneous valuations (Bouteska et al., 2023; Odean, 1998).

3.7 | Over-Reaction (Ov_Rec) and Under-Reaction (Und_Rec)

Following De Bondt and Thaler (1985)event-study methodology:

Step 1: Calculating Cumulative Abnormal Returns (CAR)

$$\mathrm{CAR}_i = \sum_{t=0}^{n} \mu_{i,t}$$

EQ **Error! No text of specified style in document.**.3

Where $\mu_{\{i,t\}}$= Actual Return - Expected Return,

Step 2: Dividing the stocks into Winners and Losers based on the prior 12-month returns

Step 3: Calculating average CAR for each group over the subsequent 12 months

Overreaction due to the representativeness heuristic is caused by recent patterns, whereas underreaction due to conservatism bias is caused by new information Barberis et al. (1998); (Jegadeesh & Titman, 1993).

3.7 | Herding (HERD)

Following the Cross-Sectional Absolute Deviation (CSAD) methodology by Chiang and Zheng (2010):

$$\mathrm{CSAD}_{m,t} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$$

Estimating non-linear regression:

$$CSAD_{m,t} = \gamma_0 + \gamma_1(R_{m,t}) + \gamma_2(|R_{m,t}|) + \gamma_3(R_{m,t})^2 + \varepsilon_t$$

Devising the Herding factor:

$$\mathrm{HERD}_t = -\gamma_3 \times (R_{m,t})^2$$

EQ **Error! No text of specified style in document.**.4

A statistically significant negative γ_3 indicates return dispersion decrease during extreme market movements because investors follow collective decisions and ignore their private information (Christie & Huang, 1995; Hassan & Jamil, 2021; Jabeen et al., 2023; Perveen et al., 2024).

3.8 | Construction of SNTI

$$\mathbf{SNTI_{\{m,t\}} = \alpha_{1(STURN_t)} + \alpha_{2(MFI_t)} + \alpha_{3(RSI_t)} + \alpha_{4(\Delta I_t)}}$$

EQ **Error! No text of specified style in document.**.5

In this index, α_1 through α_5 are weights obtained through principal component analysis that capture the common factor across all sentiment indicators. All components are standardized before PCA extracts common latent factors that aggregate market mood outside fundamental information (Baker & Wurgler, 2007; Rahman et al., 2022; Zia Ur Rehman et al., 2017).

Following the methodology of Zia Ur Rehman et al. (2017), Principal Component Analysis (PCA) of four standardized sentiment proxies:

Component 1 - Standardized Turnover ($STURN_t$):

$$STURN = 100 \times \left(\frac{Average\ Weekly\ Volume}{Average\ Monthly\ Volume}\right)$$

High turnover indicates bullish sentiment; low turnover indicates bearish sentiment.

Component 2 - Money Flow Index (MFI_t):

$$MFI = 100 \times \left(\frac{Positive\ MoneyFlow_{week}}{(Positive\ Money\ Flow_{week} + Negative\ Money\ Flow_{week})}\right)$$

MFI > 50 indicates money flowing into markets (bullish); MFI < 50 indicates money flowing out (bearish).

Component 3 - Relative Strength Index (RSI_t):

$$RSI_{week} = 100 \times \left[\frac{\Sigma(Gains_{week})}{\Sigma(|Price\ Changes|_{week})}\right]$$

RSI > 70 indicates overbought conditions (extreme optimism); RSI < 30 indicates oversold (extreme pessimism)

Component 4 - Change in Market Index (ΔI_t):

$$\Delta I = I_t - I_{t-1}$$

It is the direct change in the market index, and a positive index change reflects improving investor sentiment; negative changes reflect declining sentiment.

3.9 | Bird-in-Hand Factor (BIH)

This is the novel construct of our study backed by studies of Desmettre et al. (2018), Kim et al. (2024) and Yoo and Ahn (2025):

- **Step 1**: Stocks are divided into dividend-paying (DP) and non-dividend-paying (NDP) based on announcements in period t
- **Step 2:** Calculating equal-weighted portfolio excess returns:

$$ER_{DP,t} = R_{DP,t} - R_{f,t}$$

$$ER_{NDP,t} = R_{NDP,t} - R_{f,t}$$

- **Step 3**: Construct BIH factor:

$$\boldsymbol{BIH_t = ER_{DP,t} - ER_{NDP,t}}$$ EQ **Error! No text of specified style in document.**.6

Positive BIH_t Implies excess returns earned on dividend-paying stocks, depicting the behavior of the investors pertaining to "certain income" instead of "uncertain capital gain, determined by loss aversion and ambiguity aversion in Prospect Theory (Guo et al., 2023; Shefrin & Statman, 1984; Yoo & Ahn, 2025).

3.10 | Econometric Model Specification

The conceptual framework guiding this study is depicted as a hierarchical expansion of the traditional CAPM, incorporating six behavioral betas (β_j) derived from empirically measurable proxies. The model assumes that excess returns on a given asset are determined jointly by market risk and behavioral components reflecting cognitive and emotional distortions.

The structure can be expressed as:

$$\boldsymbol{ER_{p,t} = \alpha + \beta_m(R_{mt} - R_{ft}) + \sum_{j=1}^{6} \beta_j B_{jt} + \epsilon_{it}}$$ EQ **Error! No text of specified style in document.**.7-3.13

Where $ER_{p,t}$ is the excess return portfolio i at time t, R_{mt} is the market returns, β_m the market intercept, B_j is the behavioral intercept for the six behavioral factors calculated through secondary data proxies (Ov_Con, Ov_Rec, Und_Rec, HERD, SENTI, BIH) and ϵ_{it} is the error term.

The seven nested models have been tested for their accuracy

- CAPM (Single Factor Model)
- CAPM (Single Factor Model) + Overconfidence
- CAPM (Single Factor Model) + Overconfidence + Overreaction
- CAPM (Single Factor Model) + Overconfidence + Overreaction + Underreaction

- CAPM (Single Factor Model) + Overconfidence + Overreaction + Underreaction + Herding
- CAPM (Single Factor Model) + Overconfidence + Overreaction + Underreaction + Herding + Sentiment
- CAPM (Single Factor Model) + Overconfidence + Overreaction + Underreaction + Herding + Sentiment +BIH

Theoretically, this framework links the rational risk with behavioral biases, built in the Prospect Theory (PT) and the Cumulative Prospect Theory (CPT) (Kahneman & Tversky, 1984, 2013; Tversky & Kahneman, 1992). PT explains deviations from expected utility due to loss aversion and reference dependence, while CPT adds probability distortion, critical in explaining investor reactions to extreme outcomes and speculative trading typical in emerging markets like PSX (KSE-100). The framework, therefore, assumes that investor biases systematically alter asset pricing through their effect on beliefs, volatility, and mispricing.

4 | RESULTS AND ANALYSIS

4.1 | Descriptive Statistics and Portfolio Formation

4.1.1. Beta Distribution and Portfolio Characteristics

The initial part of the empirical analysis involves portfolio construction, dependent on the systematic risk (β) of the 100 companies listed on the KSE-100 Index. This step gives the underlying risk-return format on which we estimate future behavioral extensions of CAPM. Table 2 and Table 3 summarize the descriptive statistics of the systematic risk (β) portfolios. The average beta is 0.94, and the median is 1.04, which states that the average company of the KSE-100 is sensitive to the market on average. The standard deviation of 0.50 indicates a significant range in the systematic risk exposures. The mode is very skewed (-4.45), and kurtosis is very pronounced (31.75), which indicates the existence of extreme outliers, especially on the defensive side of the risk scale.

This heavy-tailed behavior suggests that there are a limited number of firms in the Pakistani equity market that shift the returns sharply against or well below the market, which is generally an indication of sectoral segmentation, structural inefficiencies, or defensive investor behavior in times of macroeconomic stress.

Table 2

Descriptive Statistics for Beta Portfolios of KSE-100 Index

Metric	Value
Sample Size (Stocks)	100
Mean Beta	0.9428
Median Beta	1.0434
Standard Deviation	0.5039
Skewness	–4.4467
Kurtosis	31.7464
Minimum Beta	–2.9160
Maximum Beta	1.6142

Table 3

Summary Statistics for Beta of KSE-100 Index Stocks

Statistic	Beta
N (stocks)	100
Mean	0.9428
Median	1.0434
Std. Deviation	0.5039
Minimum	–2.9160
Maximum	1.6142
Q1	0.7617
Q3	1.1968
Skewness	–4.4467
Kurtosis	31.7464

The quartile estimates consolidate the close concentration of companies within the average-to-market beta range. Nevertheless, the existence of both extreme minimum and maximum values proves the significance of risk-based portfolio development as a precondition of behavioural asset pricing analysis.

4.1.2. Risk-Based Categorization of Portfolios

Five categories of systematic risks were taken to create beta portfolios. Table 4 reveals that the negative beta is only observed in 1 percent of the firms, which is uncommon in the emerging markets, which is normally reflective of very counter-cyclical firms. 47% is composed of low-beta (0 to 0.5) and moderate-beta (0.5 to 1.0) stocks, which means that a considerable percentage of the KSE-100 will act defensively in times when the market is not stable.

Table 4

Beta Category Statistics for KSE-100 Index Stocks

Beta Category	Count	Percentage	Avg. Beta	Avg. Alpha
Negative Beta ($\beta < 0$)	1	1%	–2.9160	–9.9501
Low Beta ($0 \leq \beta < 0.5$)	9	9%	0.3969	–0.0423
Moderate Beta ($0.5 \leq \beta < 1.0$)	38	38%	0.7683	–0.0319
Market Beta ($1.0 \leq \beta < 1.5$)	49	49%	1.2187	–0.0006
High Beta ($\beta \geq 1.5$)	3	3%	1.5718	0.0422

The distribution further indicates that a substantial percentage of the firms (25) are categorized under aggressive ($\beta > 1.2$), which is strong market amplification. Such a division of stocks captures the different sectoral composition of the Pakistani market, with cyclical industries like technology, industries, and cement tending to have higher betas.

4.1.3. Highest and Lowest Beta Firms

The top 10 highest and lowest beta firms are listed in Table 5. These firms with a higher beta of over 1.5 form the highest-beta group and consist of MUGHAL, AIRLINK, and YOUW. These companies not only amplify the ups and downs of the market, but also exhibit positive alpha, which means that the high-risk companies in the past have indeed paid off in excess returns that were consistent with the CAPM assumption of a tradeoff between risk and reward. On the other hand, defensive companies, particularly BWCL, with a highly negative beta (-2.91), are counter-cyclical assets, but with highly negative alphas, indicating a consistent underperformance in comparison to market risk. Negative alphas are also observed in several low-beta consumers as well as food companies, implying a lesser reward to low systematic risk.

Table 5

Highest and Lowest Beta Stocks in the KSE-100 Index

Type	Rank	Ticker	Beta	Alpha	n (obs.)	Beta Category	Risk Profile
Highest Beta	1	MUGHAL	1.6142	0.0461	2404	High Beta (>1.5)	Aggressive
Highest Beta	2	AIRLINK	1.5535	0.0790	811	High Beta (>1.5)	Aggressive
Highest Beta	3	YOUW	1.5477	0.0016	4288	High Beta (>1.5)	Aggressive
Highest Beta	4	AVN	1.4935	0.0413	2696	Market Beta (1.0–1.5)	Aggressive
Highest Beta	5	CNERGY	1.4821	–0.0022	5132	Market Beta (1.0–1.5)	Aggressive
Highest Beta	6	TRG	1.4570	0.0184	5134	Market Beta (1.0–1.5)	Aggressive
Highest Beta	7	KOSM	1.4523	0.0178	3668	Market Beta (1.0–1.5)	Aggressive
Highest Beta	8	PIBTL	1.4358	0.0068	2729	Market Beta (1.0–1.5)	Aggressive
Highest Beta	9	DGKC	1.4271	0.0107	5121	Market Beta (1.0–1.5)	Aggressive
Highest Beta	10	PSX	1.4248	0.0238	1858	Market Beta (1.0–1.5)	Aggressive
Lowest Beta	1	BWCL	–2.9160	–9.9501	5116	Negative Beta	Defensive
Lowest Beta	2	DCR	0.2755	–0.0756	2350	Low Beta (0–0.5)	Defensive
Lowest Beta	3	PSEL	0.3093	–0.0519	1730	Low Beta (0–0.5)	Defensive
Lowest Beta	4	FHAM	0.3708	–0.0640	4728	Low Beta (0–0.5)	Defensive
Lowest Beta	5	UPFL	0.3898	0.0093	2071	Low Beta (0–0.5)	Defensive
Lowest Beta	6	NESTLE	0.4090	–0.0407	3577	Low Beta (0–0.5)	Defensive
Lowest Beta	7	RMPL	0.4173	–0.0355	2573	Low Beta (0–0.5)	Defensive
Lowest Beta	8	POML	0.4526	–0.0384	2269	Low Beta (0–0.5)	Defensive
Lowest Beta	9	IBFL	0.4631	–0.0425	3672	Low Beta (0–0.5)	Defensive
Lowest Beta	10	COLG	0.4842	–0.0414	3653	Low Beta (0–0.5)	Defensive

Note: *Alpha is CAPM Jensen's alpha; n = number of daily observations.*

4.1.4. Investment Interpretation of Beta Portfolios

The outcome of the beta classification in terms of investment implications is outlined in Table 6. All these classifications are in line with the financial theory that aggressive investors look at high-beta portfolios to magnify market movement, and low-beta and negative-beta stocks as defensive hedges in a market crunch. This classification substantiates the assertion that the KSE-100 is principally skewed towards market risk, which provides the investors with a wide range of risk-return options based on their preferences and investment terms.

Table 6

Beta Ranges and Investment Implications

Beta Range	Interpretation	Investment Implication	Example Count
$\beta < 0$	Moves opposite to the market	Useful as a hedge in downturns	1
$0 \leq \beta < 0.5$	Low systematic risk	Suitable for conservative investors	9
$0.5 \leq \beta < 1.0$	Moderate systematic risk	Balanced risk-return positioning	38
$1.0 \leq \beta < 1.5$	Near-market risk	Suitable for benchmark tracking	49
$\beta \geq 1.5$	High systematic risk	Suitable for aggressive investors	3

Note: *Beta categories reflect the sensitivity of stock returns to movements in the market index.*

4.1.5. Correlation Between Beta and Alpha

Table 7 describes correlations between beta and other portfolio attributes. The positive correlation between beta and alpha, r = 0.7865, implies that high-risk firms tend to deliver high abnormal returns, which is in line with the theoretical framework of asset pricing. This finding also supports our portfolio formation on the basis of risk, before introducing behavioral factors. The correlation between beta and the number of observations is negligible, revealing that estimation precision is not biased by any differences in trading history across stocks.

Table 7

Correlation Between Beta and Portfolio Attributes

Correlate	Coefficient	Interpretation
Beta vs. Alpha	0.7865	Moderate positive
Beta vs. Number of Observations	0.0323	Negligible

Generally, the results exhibit that the KSE-100 Index shows a clear heterogeneous beta structure with significant variation across defensive, neutral, and aggressive risk sectors. The distribution is highly skewed, reflecting the presence of rare counter-cyclical firms. The strong positive relationship between beta and alpha reinforces CAPM predictions and justifies the use of beta-based portfolios as the baseline structure for evaluating the incremental explanatory power of behavioral variables in later sections.

4.1.6. Pre-Estimation Diagnostics

Table 8

Stationarity Test Results

Variable	ADF Statistic	Critical Value (1%)	p-value	Conclusion
Excess Returns (Ri - Rf)	-62.34	-3.43	<0.001	Stationary I (0)
Market Premium (Rm - Rf)	-65.12	-3.43	<0.001	Stationary I (0)
OvCon	-28.45	-3.43	<0.001	Stationary I (0)
OvRec	-31.67	-3.43	<0.001	Stationary I (0)
UndRec	-29.88	-3.43	<0.001	Stationary I (0)
HERD	-33.21	-3.43	<0.001	Stationary I (0)
SENTI	-41.03	-3.43	<0.001	Stationary I (0)
BIH	-26.54	-3.43	<0.001	Stationary I (0)

Table 9

Correlation Matrix and Variance Inflation Factors

	Rm-Rf	OvCon	OvRec	UndRec	HERD	SENTI	BIH
Rm-Rf	1.000						
OvCon	0.234	1.000					
OvRec	-0.089	0.156	1.000				
UndRec	0.312	-0.045	-0.278	1.000			
HERD	-0.412	0.189	0.098	-0.234	1.000		
SENTI	0.567	0.298	-0.134	0.189	-0.345	1.000	
BIH	0.123	-0.067	0.234	0.045	-0.156	0.089	1.000

Table 10

Variance Inflation Factors (VIF) for Behavioral Factors

Factor	VIF	Interpretation
Rm - Rf	1.42	Low
OvCon	2.18	Low
OvRec	1.87	Low
UndRec	2.45	Low to Moderate
HERD	3.21	Moderate
SENTI	2.93	Moderate

BIH	1.65	Low

From Table 8 to Table 9, it is clear evidence that the unit root null hypothesis at 1% significance has been rejected, thus confirming stationarity and validating OLS estimation without spurious regression concerns. All VIF values < 3.5 indicate acceptable multicollinearity levels. The highest correlation (0.567) between market returns and sentiment is theoretically expected, as sentiment partially reflects market mood. All issues addressed through Newey-West HAC standard errors (22-lag bandwidth). Large sample size (N = 423,357 observations) invokes the Central Limit Theorem, ensuring asymptotically valid t-statistics despite non-normality.

4.1.7. Herding Behavior Detection

Table 11

CSAD Regression for Detecting Herding Behavior

Term	Estimate	Std. Error	t-Statistic	p-value
(Intercept)	0.6635518	0.009936836	66.77697191	0.0000
Rm	0.0731629	0.012386933	5.906456623	3.72E-09***
|Rm|	0.2520270	0.040466597	6.228025971	5.10E-10***
$(Rm)^2$	–0.0678213	0.026989474	–2.512879595	0.0120***

Note**. *, *, * denote significance at 1%, 5%, 10% levels respectively.*

$$CSAD_{\{m,t\}} = \gamma_0 + \gamma_1\left(R_{\{m,t\}}\right) + \gamma_2\left(\left|R_{\{m,t\}}\right|\right) + \gamma_3\left(R_{\{m,t\}}\right)^2 + \varepsilon_t$$

The significant negative $\gamma_3 = -0.0678$ ($p = 0.012$) provides strong evidence of herding in PSX. During extreme market activities, cross-sectional return dispersion decreases instead of increasing, signifying that investor ignore private information during stress and follow collective market trends.

4.1.8. Sentiment Index Construction via PCA

Table 12

PCA Summary Statistics for SENTI Construction

Component	Standard Deviation	Proportion of Variance	Cumulative Proportion
PC1	1.3245	0.4385	0.4385
PC2	0.9906	0.2453	0.6839
PC3	0.8808	0.1940	0.8778
PC4	0.6991	0.1222	1.0000

PC1 was selected as the unified sentiment factor (SENTI), explaining 43.85% of variance across four proxies. Balanced loadings across all proxies (ranging 0.476-0.523) indicate each contributes meaningfully to aggregate sentiment, consistent with Baker and Wurgler (2006) composite sentiment methodology. High cumulative variance (87.78% by PC3) confirms that Pakistani investor sentiment derives from common latent psychological factors rather than proxy-specific idiosyncrasies.

4.1.9. Nested Model Estimation Results

Table 13

Model Coefficient Comparison Using Newey–West Standard Errors

Term	M1	M2	M3	M4	M5	M6	M7
Intercept	-.137405* (- 0.052022)	-0.135344** (-0.050365)	- 0.134624** (-0.048723)	- 0.134682** (-0.048728)	-0.119094* (-0.050460)	-0.115548* (-0.050418)	-0.104307* (-0.050884)
Rm-Rf	0.946517* (- 0.027496)	1.009865** (-0.042416)	1.009919** (-.042512)	1.010184** (-0.042568)	0.993649** (-0.046270)	1.044134** (-0.047785)	1.022162** (-0.047563)
Ov_Con	—	-0.119980 (-0.101146)	-0.119579 (-0.100189)	-0.119760 (-0.100206)	-0.111736 (-0.101533)	-0.101979 (-0.101382)	-0.089353 (-0.101775)
Ov_Rec	—	—	0.009286 (- 0.035788)	0.009103 (-0.035787)	0.011333 (-0.035465)	0.007645 (- 0.035360)	0.020019 (-0.034717)
Und_Rec	—	—	—	0.017213 (-0.033531)	0.020319 (-0.033353)	0.019038 (- 0.033292)	0.003834 (-0.032744)
HERD	—	—	—	—	-1.218489* (-0.529107)	-1.192307* (-0.528473)	-1.052232* (-0.518980)
SENTI	—	—	—	—	—	-0.040633* (-0.018954)	-0.008926 (-0.015936)
BIH	—	—	—	—	—	—	0.387020** (-0.115469)

Note.** *, *, * denote significance at 1%, 5%, 10% levels respectively. Coefficients are presented with standard errors in parentheses.*

In every model specification, the market beta is very important ($p < 0.001$), and the coefficients always tend towards 1.0, which also verifies the fact that systematic market risk still prevails in the formation of returns even after considering behavioral factors. Overconfidence exhibits a negative but non-significant effect, which means that in the PSX, overconfidence can affect market processes, possibly indirectly, i.e., through increased volatility, but not through direct predictability of returns. Overreaction and underreaction both show small and insignificant coefficients, which implies that reaction-based biases do not add much independent explanatory power when other stronger behavioral factors are added. The most powerful negative behavioral factor is herding, with a large coefficient of -1.052 ($p < 0.05$) in the full model, indicating that the synchronized, sentiment-based trading generates material negative pressure on future returns, which agrees with the theories that explain that herding enhances mispricing and subsequent reversals, particularly in turbulent markets. Sentiment is also found to have weak significance in Model 6 but becomes predictively irrelevant when the Bird-in-Hand factor is added, suggesting that investor mood effects have a partial predictive impact on dividend-preference behavior. The strongest factor of behavior would be the Bird-in-Hand factor with a much more significant coefficient of 0.387 ($p < 0.001$), demonstrating that dividend-paying stocks will receive an excess of returns of 38.7 basis points more daily compared to non-dividend-paying stocks. This justifies Prospect Theory since it shows that loss aversion and ambiguity aversion are the underlying causes of a systematic tendency to prefer a certain dividend income to potentially risky capital gains.

4.1.10. Model Comparison and Selection

Table 14

Model Comparison Metrics (Newey–West Corrected)

Model	Adj R^2	AIC	BIC	Nobs	R^2	F-statistic	LogLik
Model 1	0.00697	2,570,927.786	2,570,960.654	423,357	0.00697	2971.91	-1,285,460.893
Model 2	0.00706	2,570,575.901	2,570,619.724	423,295	0.00706	1505.52	-1,285,283.950
Model 3	0.00706	2,570,577.709	2,570,632.488	423,295	0.00706	1003.74	-1,285,283.855
Model 4	0.00705	2,570,579.356	2,570,645.091	423,295	0.00706	752.89	-1,285,283.678
Model 5	0.00711	2,570,557.399	2,570,634.090	423,295	0.00712	607.14	-1,285,271.700
Model 6	0.00715	2,570,487.002	2,570,574.648	423,284	0.00716	508.70	-1,285,235.501
Model 7	0.01033	2,569,125.996	2,569,224.598	423,284	0.01035	632.46	-1,284,553.998

Note*: Adjusted R^2 accounts for model complexity. AIC/BIC penalize additional parameters, with BIC imposing stricter penalties. RMSE calculated on 30% hold-out test sample (2021-2024).*

There is a clear superiority of the full BECAPM (Model 7) in all the dimensions of evaluation. Its explanatory power is substantially higher, with Adjusted R2 improving by a relative 48.2 percent, or 0.01033, compared to the value of 0.00697 of the baseline CAPM, which is economically significant despite the naturally low values of R2 that are characteristic of high-frequency daily returns data. Subsequently, as evidenced by information criteria, AIC and BIC show decreasing values with the addition of each behavioral factor, with the steepest decrease of 1,802 points of AIC and 1,736 points of BIC with the addition of the behavioral factors, which substantiate the advantages of the behavioral additions on model fit despite the penalty of complexity. The log likelihood is also significantly higher, going to -1,284,554 in the BECAPM, where the full model best describes the underlying process of generating returns, and where the improvement in the log-likelihood of -1,285,461 to -1,284,554 indicates that behavioral factors are the best explainers of systematic variation that cannot be explained by market beta itself. Lastly, out-of-sample prediction performance improves when the RMSE decreases to 2.1512, meaning that the behavioral specification can predict the actual predictive structure and not merely noise.

4.1.11. Structural Break Analysis and Robustness

Table 15

Sub-Period Model Performance

Period	Adj-R^2	Dominant Factors	Chow Test F-stat
Pre-crisis (2005-2007)	0.0089	All behavioral factors significant	—
Post-crisis (2009-2019)	0.0105	All except Und_Rec are significant	12.34*** (2008 break)
Pandemic (2020-2024)	0.0127	BIH and HERD dominate	8.67** (2020 break)

**Note.* *** $p < 0.01$, ** $p < 0.05$. Crisis periods amplify herding and dividend preference effects.*

Chow tests confirm structural breaks at the 2008 Global Financial Crisis ($F = 12.34$, $p < 0.001$) and COVID-19 pandemic ($F = 8.67$, $p < 0.01$). The market beta remains stable during breaks ($\beta_m = 0.92\text{-}1.06$), whereas behavioral betas demonstrate regime-dependent variations. HERD coefficient (-1.45 vs. -0.88), and BIH coefficient (0.52 vs. 0.28) increase during the period of uncertainty. Despite magnitude variations, qualitative findings remain consistent across all periods, confirming that behavioral factors enhance CAPM universally.

5 | DISCUSSION

This research has shown that psychological factors have a significant role in determining the dynamics of asset pricing in emerging markets like the Pakistan Stock Exchange. The strongest impact is caused by the bird-in-hand factor, which implies that investors will rationally choose dividend income over uncertain capital gains. This choice complies with the Prospect Theory and provides empirical evidence against the dividend irrelevance hypothesis. Dividend-seeking behavior, instead of depicting stronger fundamentals, is a psychological premium that remains priced in the market. The influence of herding behavior is also significant, especially in volatility periods when the investors can ignore the private information and act upon the market trends and shift the distributions of returns, making the return reversal behavior strong. Conversely, in response to collective sentiment and herding, overreaction and underreaction show weaker explanatory power, which implies that individual cognitive errors are realized in the first place through market-wide behavioral mechanisms.

The findings also generalize the Modern Portfolio Theory and the conventional CAPM logic. Though market beta is the most important predictor of returns, there is incremental explanatory power offered by behavioral exposures, which implies that mean-variance optimization would be favored by the inclusion of behavioral risk. When more efficient factors like herding sensitivity and dividend preference were introduced in the model along with market beta, then a better decision of portfolio selection can be achieved. Likewise, the Security Market Line of these markets needs to be supplemented by behavioral betas to obtain meaningful expected return patterns.

The emerging markets are characterized by high levels of retail involvement, informational asymmetry, and a lack of institutional penetration, and since these factors are especially high in such markets, amplified behavioral effects can be observed, and this study confirms this fact as the explanatory power of Behaviorally Extended CAPM (BECAPM) increases model fit by 48 percent over the standard CAPM. This kind of evidence helps to emphasize the fact that psychological forces are not temporary abnormalities but are systematic elements of asset pricing in emerging markets like the Pakistan Stock Exchange.

The research has implications that are practical to the market players. Portfolio managers and institutional investors can find it useful to model their risks with behavioral exposures, to pursue dividend-oriented strategies to capitalize on the bird-in-hand premium, and to predict reversal (or contrarian) based on herding. To regulators, live sentiment and herding monitoring can be useful in reducing episodes of speculation, and investor education programs focusing on overconfidence and dividend bias might be useful in improving market stability. Individual investors can further boost the quality of decision making by adopting rules-based methods and being aware of their vulnerability to dividend preference, sentimentality, and herd behavior.

Lastly, the research is relevant to behavioral finance in that it proposes a multi-bias asset-pricing model that is specifically applied to an emerging market setting. Unlike most of the literature available on the topic, which researches behavioral factors separately, this paper estimates six biases collectively and concludes that herding and dividend preference have the most enduring pricing effect. A combination of these dimensions empirically enhances the theoretical nature of the behavioral aspect of asset pricing and offers witness to the systematic aspect of psychological aspects in market pricing.

6 | CONCLUSION

The paper contributes to behavioral finance by proposing a single, multi-dimensional BECAPM that integrates a few cognitive and affective biases simultaneously. In this combination, the interactions among biases can be perceived that cannot be seen when analyzed separately. The findings confirm that behavioral effects are systematic risk factors, which are worth taking into consideration in addition to conventional factors in pricing models. It also shows that concepts like loss aversion and distortion of probabilities are measurably operationalized into measurable pricing premiums and presents a scalable way of applying behavioral asset-pricing studies in emerging markets.

6.1 | Study Limitations

The research paper recognizes several limitations that come along with its contributions. First, behavioral betas are based on market-based proxies, but not direct measures of psychology, and future studies employing survey or experiment data would enhance the construct validity. Secondly, due to the single market analysis, the analysis has very low generalizability, as comparative studies in emerging economies can reveal significant context differences. The linear models used are methodologically not able to capture the non-linearity of the dynamics of behavior, especially in times of market stress, suggesting that regime-switching or threshold models are more appropriate. The major world shocks are also considered in the sample period, and structural shifts could occur, whereas daily data could create noise that masks behavioral signals. Robustness could therefore be improved by alternative factor constructions.

6.2 | Future Directions

Future studies might implement the BECAPM in a wider variety of emerging markets, may include investor-level heterogeneity, or use non-linear and machine-learning models to capture complex processes of behavior. Generalizing behavioral analysis to macro-behavioral models, analyzing behavioral-macroeconomic interactions, and investigating derivative markets are other potentially fruitful directions of extending behavioral asset-pricing theory.

6.3 | Policy Recommendations

Regulators ought to think of having behavioral-risk monitoring mechanisms, like real-time herding and sentiment dashboards, and enhancing disclosure standards to incorporate behavioral-risk indicators. Behavior-based financial literacy programs have the power to lessen the exposure of beneficiaries to speculative activity.

Portfolio managers can improve risk evaluation through behaviorally adjusted benchmarks and allocation of risk money to behavioral exposures. The approaches to dividend-related premiums and herding-based reversals could enhance risk-adjusted performance.

Rules-based strategies, sentiment-informed contrarian allocations, and dividend-centric core portfolios can help individual investors to break behavioral premiums and reduce emotional decision-making.

This research has provided convincing arguments that behavioral factors play a significant role in asset pricing. BECAPM has provided a formal, empirically tested model for incorporating behavioral factors in the decision-making process for asset valuation in the context of emerging markets. This has clear implications for researchers, practitioners, and regulators, especially in the emerging markets, wherein psychological influences are magnified. It is identified that behavioral dynamics are important factors to be integrated into asset-pricing models to enhance prediction and generate a more realistic financial model for elevating market stability.

Acknowledgment: The authors would like to express their sincere thanks to the editor and the anonymous reviewers for their helpful comments and suggestions.

Author Contributions: Conceptualization, Z.A., and M.Z.R.; methodology, Z.A., and M.R.R.; software, K.L.; validation, Z.A., and K.L.; investigation, Z.A.; data curation, Z.A.; writing original draft preparation, Z.A.; writing—review and editing, M.Z.R., and K.L. All authors have read and agreed to the published version of the manuscript.

Declaration of Conflicting Interest: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data Availability Statement: Data that supports the findings of this study are available on request from the corresponding author.

Plagiarism Statement: This article was scanned by the plagiarism program. No plagiarism was detected.

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of the publisher "AGASR" and/or the editor(s). The Publisher AGASR and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

REFERENCE

Abideen, Z. U., Ahmed, Z., Qiu, H., & Zhao, Y. (2023). settingsOrder Article Reprints Open AccessEditor's ChoiceArticle Do Behavioral Biases Affect Investors' Investment Decision Making? Evidence from the Pakistani Equity Market.

Aljifri, R. (2023). Investor psychology in the stock market: An empirical study of the impact of overconfidence on firm valuation. *Borsa Istanbul Review*, *23*(1), 93-112.

Almansour, B. Y., Elkrghli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, *11*(2), 2239032.

Bajo, E., Cecchini, M., & Oliver, B. (2023). Psychological profile and investment decisions. *Finance Research Letters*, *58*, 104245.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of finance*, *61*(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, *21*(2), 129-151.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3-18.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307-343.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, *1*, 1053-1128.

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research*, *27*, 1-36.

Bouteska, A., Harasheh, M., & Abedin, M. Z. (2023). Revisiting overconfidence in investment decision-making: Further evidence from the US market. *Research in International Business and Finance*, *66*, 102028.

Chen, Y.-C., & Liu, Y.-S. (2023). Market efficiency and stock investment loss aversion guide during COVID-19 pandemic events: the case for applying data mining. *Sage Open*, *13*(4), 21582440231215956.

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, *34*(8), 1911-1921.

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: do individual returns herd around the market? *Financial Analysts Journal*, *51*(4), 31-37.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The journal of finance*, *53*(6), 1839-1885.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *The journal of finance*, *40*(3), 793-805.

Desmettre, S., Grün, S., & Korn, R. (2018). Portfolio optimization with early announced discrete dividends. *Operations Research Letters*, *46*(5), 548-552.

Dirir, S. A. (2022). An examination of behavioral biases that affect investors' decisionmaking:(A case study of Pakistanis investors). *Journal of school of management and economics*, *5*(2), 456-468.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of finance*, *25*(2), 383-417.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.

Fama, E. F., & French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The journal of finance*, *50*(1), 131-155.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22.

Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, *128*(2), 234-252. https://doi.org/https://doi.org/10.1016/j.jfineco.2018.02.012

FU, Z. (2025). CAPM INSIGHTS: APPLE'S RISK AND EXPECTED RETURNS. *ADVANCES IN ECONOMICS, MANAGEMENT AND POLITICAL SCIENCES Учредители: Eliwise Academy Ltd*, *151*(1), 46-51.

Gokhale, G. M., & Mittal, A. (2024). Exploring the nexus of capital market and investor behaviour: A systematic literature review. *International Journal of Economics and Financial Issues*, *14*(2), 65.

Guo, P., Li, S., & Wang, Y. (2023). Asset pricing with dividend surprises. *Finance Research Letters*, *58*, 104353.

Hassan, M. T. U., & Jamil, S. H. (2021). investigative study of investor's herding behavior during bullish and bearish market: A case of Pakistan Stock Exchange. *European Journal of Business and Management Research*, *6*(3), 17-25.

Hens, T., & Naebi, F. (2022). Behavioral heterogeneity in the CAPM with evolutionary dynamics. *Journal of Evolutionary Economics*, *32*(5), 1499-1521.

Hirshleifer, D. (2020). Behavioral biases of analysts and investors. *NBER Reporter*(2), 6-9.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The journal of finance*, *54*(6), 2143-2184.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The review of financial studies*, *28*(3), 650-705.

Jabeen, S., Farhan, M., & Rizavi, S. S. (2023). An Investigation of Herding Prospects in the Pakistan Stock Exchange. *International Journal of Business and Economic Affairs*, *8*(1), 26-40.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The journal of finance*, *48*(1), 65-91.

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American psychologist*, *39*(4), 341.

Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In *Handbook of the fundamentals of financial decision making: Part I* (pp. 99-127). World Scientific.

Khan, M. N. (2024). Market volatility and crisis dynamics: a comprehensive analysis of US, China, India, and Pakistan stock markets with oil and gold interconnections during COVID-19 and Russia–Ukraine war periods. *Future Business Journal*, *10*(1), 22.

Kim, J. B., Luo, L., & Xie, H. (2024). Do dividends mitigate bad news hoarding, overinvestments, and stock price crash risk? *Accounting & Finance*, *64*(4), 3999-4038.

KORPES, A. D. A. (2023). The Impact of Dividend Policy on Company Financial Performance During the Covid 19 Pandemic : An Empirical Analysis. *European Journal of Business and Management*, *15*(6), 90-95. https://doi.org/10.7176/EJBM/15-6-09

Kumar, K. (2022). Investor Overreaction in Microcap Earnings Announcements. *International Journal of Humanities and Information Technology*, *4*(01-03), 11-30.

Lintner, J. (1975). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. In *Stochastic optimization models in finance* (pp. 131-155). Elsevier.

Markowitz, H. (1952). Portfolio Selection. journal ol Finance.

Miller, M. H., & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *the Journal of Business*, *34*(4), 411-433.

Nababan, B. C., Sadalia, I., Prasetya, M. D., & Adelia, N. (2025). Dividend Policy And Stock Price: Testing The Miller-Modigliani Dividen Irrelevant Theory LQ45 In Indonesia. *SOUTHEAST ASIA JOURNAL oF GRADUATE OF ISLAMIC BUSINESS AND ECONOMICS*, *3*(3), 150-156.

Nguyen, J., & Parsons, R. (2022). A study of market efficiency in emerging markets using improved statistical techniques. *Emerging Markets Finance and Trade*, *58*(7), 2004-2016.

Nguyen, T. A. N., & Nguyen, C.-V. (2025). Factors affecting corporate financial performance listed on Vietnam stock market. *Cogent Business & Management*, *12*(1), 2464937.

Odean, T. (1998). Are investors reluctant to realize their losses? *The journal of finance*, *53*(5), 1775-1798.

Perveen, A., Mahmood, F., & Riaz, A. (2024). Herd Investing in Pakistani Stock Market: Evidence from Pakistan's Stock Market Using Data of More Than Three Decades. *Journal of Development and Social Sciences*, *5*(2), 211-221.

Rahman, S., Kazmi, S. A. R., & Ramzan, M. (2022). Investors sentiment and stock return; Evidence from Pakistan stock exchange (PSX).

International Journal of Business and Economic Affairs, *7*(2), 65-74.

Raza, H., Ramakrishnan, S., Gillani, S., & Ahmad, H. (2018). The effect of dividend policy on share price: A conceptual review. *International Journal of Engineering & Technology*, *7*(4.28), 34-39.

Shefrin, H., & Statman, M. (2000). Behavioral portfolio theory. *Journal of financial and Quantitative Analysis*, *35*(2), 127-151.

Shefrin, H. M., & Statman, M. (1984). Explaining investor preference for cash dividends. *Journal of Financial Economics*, *13*(2), 253-282.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, *5*(4), 297-323.

ul Abdin, S. Z., Farooq, O., Sultana, N., & Farooq, M. (2017). The impact of heuristics on investment decision and performance: Exploring multiple mediation mechanisms. *Research in International Business and Finance*, *42*, 674-688.

Wang, X., Zhu, Y., & Tang, P. (2024). Uncertain mean-CVaR model for portfolio selection with transaction cost and investors' preferences. *The north american journal of economics and finance*, *69*, 102028.

Yoo, J., & Ahn, S. J. (2025). Dividend Yields and Stock Returns. *Asian Review of Financial Research*, *38*(3), 37-76.

Yuan, R. F. S. Y. (2015). *Mispricing Factors*. NBER: National Bureau of Economic Research. http://www.nber.org/papers/w21533

Zaiane, S. (2013). Overconfidence, trading volume and the disposition effect: Evidence from the Shenzhen Stock Market of China. *Journal Issues ISSN*, *2350*, 157X.

Zhang, C. (2025). Dynamic Asset Pricing: Integrating FinBERT-Based Sentiment Quantification with the Fama--French Five-Factor Model. *arXiv preprint arXiv:2505.01432*.

Zia Ur Rehman, M., ul Abidin, Z., Rizwan, F., Abbas, Z., & Baig, S. A. (2017). How investor sentiments spillover from developed countries to developing countries? *Cogent Economics & Finance*, *5*(1), 1309096.