BEHAVIOURAL FINANCE AND ITS IMPLICATIONS FOR ASSET PRICING MODELS

A Dissertation submitted to the Office of the Dean, Faculty of Management in partial fulfillment of the requirements for the Master's Degree

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Certification of Authorship

I hereby corroborate that I have researched and submitted the final draft of dissertation entitled **"BEHAVIOURAL FINANCE AND ITS IMPLICATIONS FOR ASSET PRICING MODELS"** The work of this dissertation has not been submitted previously for the purpose of conferral of any degrees nor it has been proposed and presented as part of requirements for any other academic purposes. The assistance and cooperation that I have received during this research work has been acknowledged. In addition, I declare that all information sources and literature used are cited in the reference section of the dissertation.

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Report of Research Committee

Ms. **Rekha Joshi** has defended her research proposal entitled "**BEHAVIOURAL FINANCE AND ITS IMPLICATIONS FOR ASSET PRICING MODELS**" successfully. The research committee has registered the dissertation for further progress. It is recommended to carry out the work as per suggestions and guidance of supervisor Arun Neupane submits the thesis for evaluation and viva voce examination.

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APPROVAL-SHEET

We, the undersigned, have examined the thesis entitled **“Behavioural Finance and Its Implications for Asset Pricing Models”** presented by Ms. Rekha Joshi, a candidate for the degree of **Master of Business Studies (MBS)** and conducted the viva voce examination of the candidate. We hereby certify that the thesis is worthy of acceptance.

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ABBREBRIATIONS

CAPM: Capital Asset Pricing Model

NEPSE: Nepal Stock Exchange

MBS: Master of Business Studies

OLS: Ordinary Least Squares

R-squared: Coefficient of Determination

TU: Tribhuvan University

COVID-19: Coronavirus Disease 2019

PLS: Partial Least Squares

FF3FM: Fama-French Three-Factor Model

FF5FM: Fama-French Five-Factor Model

MCAPM: Modified Capital Asset Pricing Model

NBER: National Bureau of Economic Research

SPSS: Statistical Package for the Social Sciences

Abstract

This study explores the implications of behavioural finance on asset pricing models, specifically within the context of the Nepal Stock Exchange (NEPSE). Traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), often assume rational investor behavior and market efficiency. However, these models frequently overlook the psychological biases and emotions that influence investor decisions. By integrating behavioral finance factors—such as momentum, volatility, and trading volume—into an extended CAPM, this research aims to provide a more accurate representation of market dynamics in Nepal. The findings reveal that behavioral factors significantly impact stock returns, highlighting the limitations of traditional models and underscoring the necessity of incorporating behavioral insights into asset pricing frameworks. This study offers valuable implications for investors, financial advisors, and policymakers, advocating for a more comprehensive approach to understanding and predicting market behavior in emerging economies.

Keywords: Behavioural Finance, Asset Pricing Models, Nepal Stock Exchange (NEPSE), Investor Psychology, Market Dynamics.

CHAPTER I

Introduction

1.1 Background of the Study

Behavioral finance is a dynamic field that explores how psychological factors influence the behavior and decisions of investors, portfolio managers, financial experts, and other market participants (Brajković & Peša, 2015; Muradoglu & Harvey, 2012; Bakar & Yi, 2016). Unlike standard finance theory, which assumes perfect rationality, behavioral finance embraces the more realistic concept of bounded rationality, as introduced by H. A. Simon in 1955.

Insights gained from behavioral finance help financial decision-makers identify and understand their errors, learn from these mistakes, and, crucially, prevent repeating them in the future (Muradoglu & Harvey, 2012; De Bondt, Mayoral & Vallelado, 2013). Behavioral economists say that behavioral finance has made financial theory much better by explaining how people make financial decisions (Thaler, 1999).

The behavioral asset-pricing model and behavioral portfolio theory make financial theory more realistic by including concepts like mental accounting, bounded rationality, emotional and expressive benefits, and limitations on arbitrage (Shefrin & Statman, 2000). Behavioral finance theory suggests that knowing the psychology of market participants is crucial to fully understanding asset pricing and price movements (Fakhry, 2016).

Behavioral finance focuses on specific human behavior attributes and how they are used in asset pricing. Despite the existence of many asset-pricing models, their shortcomings and gaps necessitate the investigation of behavioral factors. This study attempts to model asset pricing using behavioral models. As Fakhry (2016) suggests, recognizing the influence of biases, emotions, and cognitive errors on human behavior allows for a more realistic understanding of how investors make financial decisions, potentially leading to more informed strategies.

Recent research has continued to explore these themes. For instance, Bourghelle et al. (2023) discuss the influence of investor emotions on asset prices, highlighting how market sentiment and external factors such as the COVID-19 pandemic have driven market volatility. Additionally, Boulu-Reshef et al. (2023) provide experimental analysis on investor sentiment, further highlighting the role of psychological factors in financial markets. Padmavathy (2024) examines the link between behavioral finance and stock market anomalies, emphasizing how psychological biases like overconfidence and loss aversion contribute to market inefficiencies. Akin and Akin (2024) investigate the impacts of behavioral finance on US stock market volatility, revealing significant correlations between behavioral biases and market movements. Furthermore, Yi (2024) reviews key findings and practical applications of behavioral finance, underscoring the importance of understanding investor psychology in financial decision-making.

Behavioral finance has numerous applications. In the investment world, it helps investors recognize cognitive biases and emotional factors, leading to more effective investment strategies (Barberis & Thaler, 2003). Behavioral finance helps investors understand how market prices are formed by examining the behavior of individuals and their psychological motivations. It highlights that human emotions and cognitive biases often lead to deviations from traditional finance models, which assume rational decision-making. By identifying these biases, investors can make more informed decisions and avoid common pitfalls (Amin & Pirzada, 2014; Huang et al., 2018).

For instance, in terms of asset pricing, behavioral finance reveals the underlying mechanisms and principles that drive market prices. It provides investors with more accurate references for asset pricing by considering factors such as overconfidence, herd behavior, and loss aversion (Barber & Odean, 2001; Kahneman & Tversky, 1979). These insights help investors to better gauge the true value of assets and make more rational investment choices.

Overall, behavioral finance aims to explain, study, and predict the future development of financial markets by focusing on the behavior of individuals and the psychological factors influencing their decisions. This approach offers a more comprehensive understanding of market dynamics, ultimately leading to improved investment strategies and financial outcomes (Shefrin, 2000; Shiller, 2000).

Emerging markets, such as Nepal, present unique challenges and opportunities for the application of behavioral finance. The Nepal Stock Exchange (NEPSE) is characterized by high volatility, limited liquidity, and a significant presence of individual investors who may be more susceptible to psychological biases. Understanding these behavioral factors is crucial for developing more accurate asset pricing models that reflect the realities of such markets. Traditional asset pricing models, which assume rational behavior and market efficiency, often fail to capture the complexities of investor behavior in these contexts. By integrating behavioral insights, this study aims to enhance the predictive power and relevance of asset pricing models in the Nepalese market.

Recent studies have explored the influence of behavioral biases on investment decisions and performance in the Nepalese stock market. Pokharel (2020) examined the impact of heuristic, prospect, market, and herding behaviors on investment performance, finding that market factors significantly affect investment outcomes, while heuristic and herding behaviors do not show a significant relationship. Gnawali (2021) investigated the effect of behavioral biases on individual investors' decision-making, revealing that social interaction and regulatory policies significantly influence investment decisions, whereas psychological factors have a negative relationship. Aryal (2021) focused on the effect of behavioral biases such as overconfidence, loss aversion, familiarity, and herding mentality on investment performance, concluding that only overconfidence bias significantly impacts investment performance, while other biases are negatively but not significantly related.

1.2 Problem Statement and Research Questions

Problem Statement

Traditional asset pricing models like the Capital Asset Pricing Model (CAPM) assume that investors make decisions based on logic and complete information. However, these models fail to account for the influence of psychological biases and emotions on investor behavior, particularly in the Nepalese stock market. This oversight can lead to market inefficiencies and the mispricing of assets, as investors' decisions are often driven by cognitive biases such as overconfidence, loss aversion, herding, and the disposition effect. In the context of the Nepal Stock Exchange (NEPSE), where individual investors play a significant role, understanding these behavioral biases is crucial. This research aims to address this gap by investigating the impact of behavioral biases in the Nepalese stock market and their impact on asset pricing models. By quantifying these influences, the study seeks to develop a more realistic model that incorporates behavioral factors alongside traditional risk measures. This approach can lead to improved investment decision-making, more informed financial advice, and potentially better regulatory frameworks for the Nepalese market.

Research Questions

This study explores the influence of behavioral finance on asset pricing models, particularly within the context of the Nepal Stock Exchange (NEPSE). To address the identified research gaps, the study focuses on the following questions:

i. How prevalent are behavioral biases, such as overconfidence, loss aversion, herding, and the disposition effect, among individual investors in Nepal, as evidenced by empirical data from the Nepal Stock Exchange (NEPSE)?
ii. How do trading volume, market sentiment, and momentum affect investment decisions and stock returns in the Nepalese stock market?
iii. How effectively do traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), capture the influence of behavioral factors in the Nepalese context?
iv. Can a behavioral asset pricing model be developed to enhance the accuracy of asset pricing in the Nepalese market by incorporating factors like trading volume, market sentiment, and momentum?

These questions aim to provide insights into how psychological factors shape investment behavior and to propose a more comprehensive framework for asset pricing in emerging markets like Nepal.

Research Hypotheses

The following hypotheses have been formulated to investigate the impact of behavioral finance on asset pricing models:

H0: Behavioral finance has an insignificant implication in asset pricing models.
H1: Behavioral finance has a significant implication in asset pricing models.

1.3 Objective of the Study

The primary aim of this study is to evaluate the impact of behavioral finance on asset pricing models. The specific objectives are:

i. To analyse the implications of behavioral finance in asset pricing models.
ii. To examine the relationships between behavioral finance and asset pricing models.
iii. To assess the status of behavioral asset pricing models in the Nepalese market.

1.4 Significance of the Study

This thesis holds significant value for several reasons:

i. **Enhanced Understanding of Behavioral Finance:** This research examines the prevalence and impact of behavioral biases among Nepalese investors, providing deeper insights into how psychological factors influence investment decisions and asset pricing in the Nepalese stock market.
ii. **Improvement of Asset Pricing Models:** The study aims to develop a more realistic asset pricing model that incorporates behavioral factors alongside traditional risk measures. This can lead to more accurate asset pricing and better investment decision-making.
iii. **Informed Financial Advice:** The insights provided by this research can benefit financial advisors and investors, leading to more informed and effective investment strategies that account for behavioral biases.
iv. **Policy and Regulatory Implications:** The findings can inform policymakers and regulators about the behavioral dynamics in the stock market, potentially leading to improved regulatory frameworks that enhance market efficiency and protect investors.
v. **Contribution to Academic Literature:** This thesis fills a gap in the existing literature on behavioral finance in the context of the Nepalese stock market, providing a foundation for future research in this area.
vi. **Practical Applications:** The proposed behavioral asset pricing model can be utilized by practitioners in the finance industry to better understand market movements and investor behavior, leading to more robust financial planning and risk management.

1.5 Limitations of the study

This study will focus on the issues raised in the research questions, acknowledging several limitations:

i. The research may be constrained by the availability and reliability of stock trading data from the Nepalese stock market.
ii. The findings may be specific to the Nepalese market and may not be generalizable to other contexts.
iii. Accurately capturing behavioral biases through stock trading data presents challenges.
iv. The proposed model may not encompass all relevant factors and relies heavily on the quality of the trading data.
v. The study does not focus on individual investors, which may limit the scope of the findings.
vi. Behavioral factors such as trading volume, market sentiment, and momentum are complex and may not be fully captured in the model.

1.6 Organization of the Study

This thesis, titled "***Behavioral Finance and Its Implications for Asset Pricing Models***", is organized into five chapters. Each chapter builds upon the preceding one to provide a comprehensive exploration of the topic. The chapter plan is as follows:

Chapter 1: Introduction

This chapter provides an overview of the study, including the background, problem statement, research questions, objectives, and significance. It outlines the scope and limitations of the research and sets the foundation for understanding the implications of behavioral finance on asset pricing models.

Chapter 2: Literature Review

The literature review explores key theories and studies in behavioral finance and traditional asset pricing models. It discusses critical concepts such as behavioral biases, their influence on investor behavior, and their implications for asset pricing. The chapter identifies gaps in existing research, emphasizing the need for integrating behavioral insights into asset pricing models in the context of the Nepalese stock market.

Chapter 3: Research Methodology

This chapter details the research design, including the population and sample selection, data collection and processing methods, and the variables and models used in the study. It introduces the behavioral asset pricing model developed for the research and explains how behavioral finance factors such as momentum, volatility, and trading volume are integrated into traditional models.

Chapter 4: Results and Discussion

The results and discussion chapter presents the analysis of data collected from the Nepal Stock Exchange (NEPSE). It highlights the major findings, interprets the results in light of existing literature, and demonstrates how behavioral factors influence stock returns and asset pricing. Key discussions focus on the limitations of traditional models and the predictive power of behavioral insights.

Chapter 5: Summary and Conclusion

The final chapter summarizes the key findings of the research and discusses their theoretical and practical implications. It provides recommendations for policymakers, investors, and future researchers interested in behavioral finance and asset pricing models. The chapter concludes with suggestions for further studies in the context of emerging markets like Nepal.

CHAPTER II

Review of Literature

This chapter reviews and discusses theories and empirical studies related to behavioral finance and its implication on asset pricing models.

2.1 Conceptual Review

Behavioral finance extends the principles of behavioral economics, emphasizing the significant role of human emotions and psychology in financial decision-making. Unlike traditional finance, which assumes investors act rationally, behavioral finance offers a more detailed understanding by acknowledging both rational and irrational investor behaviors. Behavioral finance aims to explain how investors make decisions by combining ideas from different fields—psychology, sociology, and anthropology. This interdisciplinary field sheds light on recurring behavioral biases and challenges the assumption of perfectly rational markets, offering insights into the mechanisms behind investor behavior. Behavioral finance combines psychological theories with conventional economics to explain why investors frequently make irrational financial decisions.

Traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), assume rational investors and efficient markets. However, behavioral finance challenges these assumptions by emphasizing the impact of cognitive biases and emotions on investor behavior and market outcomes (Thaler, 1999).

2.1.1 Behavioral Finance: Key Concepts

Behavioral finance extends the principles of behavioral economics by focusing on the emotions and psychology of investors. This field helps us understand both the rational and irrational behaviors of investors, as well as the cognitive and social psychological factors that influence their investment decisions. As an interdisciplinary research area, behavioral finance effectively integrates concepts and findings from psychology, sociology, and anthropology. It highlights numerous recurring behavioral biases among investors, providing a new understanding of how these mechanisms function.

By examining the psychological and emotional biases that influence financial decisions, behavioral finance challenges the assumption of perfect rationality in traditional finance. This multidisciplinary field introduces a range of psychological biases that often result in market inefficiencies, thereby challenging traditional finance theories.

Behavioral finance usually covers five key concepts:

Mental Accounting: Mental accounting refers to the habit of individuals to separate money into various "accounts" based on subjective factors, like its source or purpose. For example, investors may treat a tax refund differently from regular income, even though both are simply forms of money. This segmentation can lead to irrational financial behavior, like overspending in one category while conserving in another (Thaler, 1999).

Herd Behavior: Investors often follow the actions of the majority, particularly during periods of market volatility. Herd behavior can lead to extreme market trends, such as bubbles or crashes, where investors collectively chase rising stocks or sell off in panic. This phenomenon is particularly evident in the context of the stock market, where price movements are often amplified by group psychology (Shiller, 2015).

Emotional Gap: Decision-making can be strongly influenced by emotions such as fear, anger, excitement, or anxiety. This “emotional gap” often leads to irrational financial choices, such as panic-selling during a market downturn or overinvesting during a bullish period (Loewenstein & Lerner, 2003).

Anchoring: Investors tend to “anchor” their decisions on certain reference points, such as a stock’s previous high price, even when that information is no longer relevant. For instance, an investor might hold onto a losing stock, believing it will return to its past peak, despite contrary evidence (Tversky & Kahneman, 1974).

Self-Attribution Bias: Investors often exhibit overconfidence in their financial knowledge or abilities. This bias leads to excessive trading and poor diversification, as individuals mistakenly believe they can “beat the market” (Barber & Odean, 2001).

Behavioral finance assumes that investors are not purely rational; instead, they are influenced by psychological factors and often display self-control inconsistencies. These biases can have profound impacts on financial markets and asset pricing.

Behavioral finance assumes that financial participants aren't perfectly rational or entirely self-controlled but are instead influenced by psychological factors, with varying degrees of self-control. Financial decisions often depend on an investor's mental and physical health. As an investor's overall health changes, their mental state is also affected, which in turn impacts their decision-making and rationality regarding real-world issues, including financial matters.

Behavioral finance can be examined from multiple viewpoints. Stock market returns are a key area where psychological behaviors are believed to influence market outcomes and returns, but there are also many other aspects to consider. The goal of classifying behavioral finance is to understand why people make specific financial decisions and how these choices impact markets.

Behavioral finance is a multidisciplinary field that aims to deepen our understanding of human behavior in financial contexts by incorporating insights from psychology, sociology, and anthropology. It has shown that many behavioral biases appear repeatedly among investors, highlighting patterns that financial research needs to consider.

Behavioral finance consists of two reason that people do not find about their financial attitudes that investigate feeling of investor that are deviated in attitude these deviations are consists of two subcategories cognitive deviation and emotional deviation. Theories in behavioral finance include overconfidence, loss aversion, inertia, financial cognitive dissonance, regret theory, and prospect theory.

2.1.2 Theories of Behavioral Finance

Behavioral finance provides various theories that explain why investors deviate from rational financial behavior. Some prominent theories include:

Prospect Theory: Developed by Kahneman and Tversky (1979), prospect theory posits that investors are risk-averse when it comes to gains but become risk-seeking when faced with potential losses. This asymmetry helps explain why investors may hold onto losing stocks for too long, hoping to recover losses, while quickly selling winning stocks to lock in profits. The theory also introduces the "certainty effect," where individuals disproportionately weigh outcomes that are perceived as certain over those that are merely probable.

Regret Theory: Investors often avoid making decisions to sidestep the emotional pain of regret if their investment choice turns out poorly. This can lead to inertia in decision-making, where investors refrain from taking action—such as selling a losing stock—out of fear that they will later regret the decision (Shefrin & Statman, 1985).

Anchoring: Anchoring, another concept introduced by Kahneman and Tversky (1974), occurs when individuals base their financial decisions on irrelevant or outdated information. For example, investors may continue to rely on a stock's historical high price as a benchmark, even when market conditions have significantly changed.

Overconfidence Bias: Investors tend to overestimate their abilities to predict market movements, leading to excessive trading, under-diversification, and increased risk (Barber & Odean, 1999). This bias can result in inflated market bubbles or deeper downturns as overconfident investors fail to recognize market signals accurately.

Cognitive Dissonance: Cognitive dissonance occurs when investors face conflicting information that challenges their prior beliefs. To avoid the discomfort of this dissonance, investors may irrationally hold onto failing investments, ignoring new data that suggests they should sell (Festinger, 1957). This bias contributes to the persistence of market inefficiencies.

Loss Aversion: Investors are far more sensitive to losses than gains of the same magnitude. This bias, as explained in prospect theory, can lead to suboptimal decisions, such as holding onto a losing stock for too long to avoid realizing a loss (Kahneman & Tversky, 1979). Loss aversion plays a crucial role in behavioral finance and asset pricing anomalies (Thaler, 1985).

2.1.3 Asset Pricing Models

Asset pricing models provide frameworks for predicting the expected return of investments based on their risk profiles. Traditional models assume rationality and efficient markets, while behavioral finance critiques these assumptions. The two primary categories are:

Single-Factor Models: The Capital Asset Pricing Model (CAPM) is a classic single-factor model that calculates expected returns based on an asset's beta—its volatility relative to the market. CAPM is grounded in the assumption that investors are rational and markets are efficient, but behavioral finance research suggests this model may not fully capture investor behavior (Fama & French, 2004).

Multi-Factor Models: Models like the Fama-French Three-Factor Model extend CAPM by incorporating additional risk factors, such as company size and value. These factors attempt to account for market anomalies that CAPM cannot explain, acknowledging that the market is not purely efficient (Fama & French, 1993).

2.1.4 Behavioral Finance's Implication on Asset Pricing Models

Behavioral finance presents significant challenges to traditional asset pricing models, particularly the Capital Asset Pricing Model (CAPM), by highlighting how psychological biases contribute to market inefficiencies and anomalies. These biases can distort asset prices and lead to deviations from their intrinsic values, creating opportunities for mispricing. The key implications of behavioral finance for asset pricing models include:

Exposing Market Inefficiencies: Behavioral finance underscores that markets are not always efficient. Psychological biases, such as overconfidence and herd behavior, often distort asset prices and lead to deviations from their intrinsic values. These inefficiencies can persist over time, contrary to the assumptions of traditional models that expect markets to correct themselves quickly (Barberis & Thaler, 2003).

Explaining Market Anomalies: Traditional asset pricing models fail to account for persistent market anomalies such as momentum and reversal effects. Behavioral finance theories propose that biases, including anchoring and herd behavior, are the driving forces behind these anomalies. These biases can lead to price distortions that do not align with traditional valuation methods, suggesting that investor psychology plays a central role in shaping market outcomes (Jegadeesh & Titman, 1993).

Incorporating Investor Sentiment: While traditional models assume that investors are rational and risk-averse, behavioral finance acknowledges that emotions such as fear and euphoria strongly influence investor behavior. These emotional factors can drive asset bubbles and crashes, causing extreme price movements that are difficult to explain using traditional models (Baker & Wurgler, 2007).

Behavioral Asset Pricing Models: Traditional models overlook the significant role of investor psychology in asset pricing. In response, researchers have developed behavioral asset pricing models that integrate psychological factors to offer a more realistic framework for understanding asset prices. The Behavioral Asset Pricing Model (BAPM), for example, combines elements of traditional asset pricing models with insights from behavioral finance to account for biases such as overconfidence and loss aversion (Shiller, 2000).

By acknowledging the influence of behavioral finance, asset pricing models can be adapted to better capture real-world market dynamics. This leads to a more nuanced understanding of how risk and return interact, potentially resulting in more accurate valuations and more informed investment decisions.

2.1.5 Implications for Asset Pricing Models

Traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), operate under the assumption that investors are rational and markets are efficient. However, behavioral finance introduces several challenges to these assumptions and has important implications for asset pricing models:

Deviation from Rationality: Behavioral biases, including overconfidence, loss aversion, and herding behavior, can lead to asset prices deviating from their intrinsic values. These biases create opportunities for mispricing, as investors are often influenced by psychological factors rather than purely rational decision-making.

Limits to Arbitrage: While arbitrageurs theoretically can profit from market inefficiencies, behavioral biases can limit their ability to exploit mispricing effectively. Psychological factors, such as the fear of loss or the inability to fully correct market distortions, may prevent arbitrageurs from correcting inefficiencies, allowing mispricing to persist longer than traditional models would predict.

Investor Sentiment: Investor sentiment, which is shaped by emotions like fear, euphoria, and herd behavior, can significantly influence asset prices. This often results in short-term price fluctuations and market bubbles, which traditional models struggle to explain. Behavioral finance highlights how sentiment-driven movements, such as speculative booms or market crashes, can distort asset prices in ways that are not captured by traditional theories.

Risk Perception: Behavioral finance also reveals that investors' perceptions of risk can be distorted by emotional biases and cognitive errors. This distortion affects their required rate of return and influences asset pricing. For example, investors may overestimate or underestimate risk based on recent experiences, leading to mispricing in the market.

In the context of Nepal, there has been a growing interest in understanding how behavioral biases influence stock trading behavior in the Nepal Stock Exchange (NEPSE). Studies have shown that local investors often exhibit herd behavior and overconfidence, contributing to market volatility and inefficiencies (Gurung, 2020). This has led to calls for incorporating behavioral insights into asset pricing models to better reflect the realities of emerging markets like Nepal.

Integrating behavioral insights into asset pricing models allows for a more comprehensive view of market dynamics. By incorporating psychological factors, these models can better capture the complexities of investor behavior and the impact of sentiment, risk perception, and market anomalies on asset pricing. This approach provides a more accurate picture of how risk and return interact, enabling investors to better navigate the complexities of emerging markets like Nepal, where psychological factors play a critical role in shaping market outcomes.

2.2 Review of Related Studies

In their influential 1993 study, Fama and French introduced the Three-Factor Model, which proposes that stock returns are influenced by three primary risk factors: market risk, size, and value. The study challenges the traditional Capital Asset Pricing Model (CAPM) by offering a broader framework for understanding asset pricing.

Jegadeesh and Titman (1993) investigate momentum and reversal effects in stock returns, attributing these anomalies to behavioral factors such as herding and anchoring. They observe that stocks which have shown good performance in the past often keep performing well in the short term, while those with poor past performance tend to keep performing poorly. These findings challenge the traditional view of market efficiency and suggest that investor behavior, driven by psychological biases, plays a significant role in asset pricing. Their research highlights the need for asset pricing models that account for these behavioral factors to better explain stock return patterns (Jegadeesh & Titman, 1993).

In his book "Beyond Greed and Fear," Shefrin (2000) explores the psychological factors influencing investor behavior and their implications for asset pricing. He examines various behavioral biases, including overconfidence, loss aversion, and mental accounting, and their effects on market efficiency.

Shefrin argues that traditional asset pricing models need to be modified to incorporate these behavioral insights to better reflect real-world investor behavior. His work provides a detailed analysis of how psychological factors can lead to market anomalies and inefficiencies, challenging the assumptions of rationality in traditional finance (Shefrin, 2000).

In "Irrational Exuberance," Shiller (2000) examines how psychological factors and investor sentiment contribute to market bubbles and crashes. He argues that traditional asset pricing models fail to account for the impact of investor psychology on market dynamics. Shiller provides empirical evidence of how irrational behavior, driven by emotions such as greed and fear, can lead to significant deviations from fundamental values. His work emphasizes the importance of incorporating behavioral finance insights into asset pricing models to better predict and understand market movements, particularly during periods of extreme market conditions (Shiller, 2000).

Barberis and Thaler (2003) provide a comprehensive survey of behavioral finance, discussing how psychological biases such as overconfidence and representativeness affect financial decisions and asset prices. They highlight the limitations of traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), in explaining market anomalies. The authors propose behavioral asset pricing models as more realistic alternatives that incorporate psychological factors to better understand market dynamics. Their work underscores the importance of integrating behavioral insights into financial models to account for investor behavior that deviates from rationality (Barberis & Thaler, 2003).

Brown and Cliff (2005) examine the link between investor sentiment and asset valuation. Their analysis, based on a direct survey measure of sentiment, reveals a predictive power for market returns over a 1-3 year horizon. This sentiment measure also sheds light on deviations from intrinsic value identified by other valuation models. The authors acknowledge two interpretations: a new valuation factor or a direct influence of sentiment on stock prices. Regardless of interpretation, their findings support the role of investor sentiment in explaining asset mispricing and potentially market bubbles (Brown & Cliff, 2005). This aligns with behavioral finance theories and suggests the need to incorporate sentiment into asset pricing models.

Baker and Wurgler (2007) examine the role of investor sentiment in the stock market, demonstrating how emotions like euphoria and fear can drive asset prices away from their fundamental values. They argue that traditional models fail to account for the impact of investor sentiment on market prices, leading to mispricing and market inefficiencies. Their research emphasizes the need to incorporate sentiment measures into asset pricing models to better understand and predict market movements. This study provides empirical evidence that investor sentiment significantly influences stock returns, highlighting the limitations of traditional models that assume rational behavior (Baker & Wurgler, 2007).

Johnston and Pennypacker (2009) discuss various methods for data collection and measurement assessment in behavioral research. Although it primarily focuses on behavior analysis, the principles can be applied to financial markets to measure behavioral factors using historical trade data. The study emphasizes the importance of reliable data collection methods to accurately assess the impact of behavioral biases (Johnston & Pennypacker, 2009).

Amin and Pirzada (2014) explore the potential of behavioral finance to explain property market dynamics, arguing that traditional models overlooking investor psychology are inadequate. Their review highlights key behavioral finance concepts like investor sentiment and limitations to arbitrage, alongside specific human behavior theories (e.g., prospect theory, overconfidence) that may influence property valuations and decision-making. The authors emphasize the importance of understanding investor sentiment for explaining market behavior and suggest that a behavioral framework could inform wiser property investment decisions. However, the paper lacks a clearly defined research question and offers a descriptive, rather than prescriptive, analysis of behavioral finance applications. Future research is warranted to develop a more actionable framework for integrating these principles into property investment strategies (Amin & Pirzada, 2014).

Huang et al. (2018) investigate investor sentiment across five asset classes: stocks, bonds, commodities, currencies, and housing. They utilize sentiment measures derived from news and social media to show that each market is influenced by its own sentiment. Interestingly, the study reveals cross-market predictive linkages. For instance, stock market returns are influenced by bond sentiment, while currency sentiment impacts bond returns. The authors further employ Partial Least Squares (PLS) to create a combined sentiment index, demonstrating that incorporating information from all markets improves return predictability compared to individual sentiment measures. These findings suggest that sentiment can be contagious across asset classes, with important implications for understanding asset return dynamics (Huang et al., 2018).

Lekovic (2019) challenges traditional finance's perfect rationality assumption in Economic Horizons. He proposes behavioral finance, incorporating bounded rationality and psychology, as a more realistic approach. The paper explores behavioral portfolio theory and the behavioral asset-pricing model as alternatives, highlighting the influence of psychology on investment decisions. While acknowledging their potential to improve financial models, Lekovic emphasizes the need for further research to definitively compare them to traditional approaches.

Chandrakala & Kamal (2019) bridge theory and practice by examining how behavioral finance concepts like overconfidence and regret aversion influence investment decisions among Bangalore investors (India). Their survey (n=181) explores how psychology impacts investor behavior, offering real-world insights into behavioral finance's practical application. This study strengthens our understanding of investor decision-making through a behavioral lens.

Frydman et al. (2019) explore how sentiment impacts stock return forecasts. They argue investor optimism/pessimism influences the weight given to fundamentals (dividends, interest rates) in forecasts. The study reveals that positive news with optimism (or negative news with pessimism) strengthens the forecasted impact on returns, but this effect weakens when sentiment is neutral or conflicts with the news. Interestingly, sentiment shows little correlation to economic activity, suggesting non-fundamental drivers. The study challenges traditional models and highlights the need for further research on the theoretical underpinnings of sentiment's influence on return forecasts (Frydman et al., 2019).

Frydman et al. (2019) explore how investor sentiment impacts stock return forecasts, highlighting the need for further research on the theoretical underpinnings of sentiment’s influence on return forecasts. They find that investor optimism or pessimism significantly affects the weight given to fundamentals such as dividends and interest rates in return forecasts. The study reveals that positive news coupled with optimism (or negative news with pessimism) strengthens the forecasted impact on returns, while neutral or conflicting sentiment weakens this effect. Their research suggests that incorporating sentiment measures into asset pricing models can improve their predictive power and provide a more comprehensive understanding of market dynamics (Frydman et al., 2019).

Khudoykulov (2020) examines the applicability of prominent asset-pricing models in the Indian equity market. The study evaluates the Capital Asset Pricing Model (CAPM), Fama-French Three-Factor Model (FF3FM), and Fama-French Five-Factor Model (FF5FM) for their ability to explain average stock returns from January 2009 to November 2018. The analysis highlights the limitations of CAPM as a single-factor model and suggests that FF3FM and FF5FM provide a better fit. Furthermore, the study reveals that size and value factors significantly contribute to explaining return variations, while profitability and investment factors have limited explanatory power. These findings contrast with some prior research on the Indian market. The study concludes that FF5FM outperforms CAPM and FF3FM in the Indian context, but acknowledges that even FF5FM may not capture all return variations. Future research is recommended to explore additional factors specific to the Indian market (Khudoykulov, 2020).

Nasiri et al. (2021) investigated the role of behavioral variables in asset pricing using data from the Tehran Stock Exchange. Challenging traditional models that solely focus on risk and return, they employed a Fama-Macbeth approach to demonstrate a significant and positive impact of behavioral variables on stock returns. The study identified accounting information risk, investor trading behavior, and investor sentiment as key factors influencing firm stock returns. These findings suggest that investors and market analysts should consider these behavioral factors alongside traditional risk-return models to make more informed investment decisions. By incorporating behavioral finance into asset pricing models, Nasiri et al. (2021) highlights the potential for a more comprehensive understanding of market dynamics.

Mangee (2023) explores Knightian uncertainty, the impact of unforeseeable events, on stock prices. Unexpected corporate events, used as a proxy for this uncertainty, become more frequent as the gap between stock prices and their intrinsic value widens. This suggests greater uncertainty about future developments fuels larger deviations from fundamental value. The study also finds unexpected events significantly impact expected returns, especially in the long term. These findings emphasize the need to consider Knightian uncertainty in explaining stock prices and for investors to adapt their risk assessment as unexpected events occur (Mangee, 2023).

Chen et al. (2023) proposes a theoretical and empirical framework for asset pricing and corporate finance based on behavioral factors. They argue that traditional models often overlook the psychological aspects of investor behavior, which can lead to mispricing and market inefficiencies. Their model incorporates behavioral biases such as overconfidence and loss aversion to better explain asset prices and corporate financial decisions (Chen et al., 2023).

Padmavathy (2024) examines the link between behavioral finance and stock market anomalies. Challenging traditional models, the study highlights how psychological biases like overconfidence and loss aversion lead to irrational investor behavior and contribute to market inefficiencies. These biases, coupled with emotions like fear and greed, can exacerbate market booms and busts. The research also explores the influence of social dynamics such as herd mentality on market anomalies. Padmavathy emphasizes the importance of understanding these behavioral factors for investors and regulators alike, suggesting the need for sophisticated models and customized investment strategies to navigate complex financial environments.

Yi (2024) reviews the field of behavioral finance, highlighting key findings and practical applications. The review covers prominent theories like loss aversion and framing effects, emphasizing their influence on investor decision-making and potential market anomalies. Yi identifies a gap in research on the interactions between these phenomena and their overall impact. The review concludes by calling for future research to utilize quantitative models to explore the dynamic mechanisms behind these behavioral biases, aiming to improve financial market stability and efficiency (Yi, 2024).

In their 2024 study, Gorzon, Bormann, and von Nitzsch offer a detailed overview of the current literature on behavioral biases and their measurements. The authors created a behavioral factor model to analyse portfolio performance from a behavioral finance perspective. The authors identified 11 behavioral bias factors and 29 associated measurements, including the disposition effect, under-diversification, home bias, local bias, lottery stock preference, trend chasing, overtrading, and trade clustering. These factors were measured using historical trade data to assess their impact on portfolio performance (Gorzon, Bormann, & von Nitzsch, 2024).

Backtesting is a method used to evaluate the effectiveness of trading strategies using historical data. While it primarily focuses on understanding the interplay between risk and return, it also considers psychological factors influencing trading decisions. This approach helps in quantifying the impact of behavioral biases on trading strategies by simulating them across historical market conditions (Groette, 2024).

Akin and Akin (2024) explored how behavioral finance influences US stock market volatility, especially regarding market anomalies. Using time-series analysis over a decade, they examined the S&P 500, real interest rates, consumer confidence, market volatility, and credit default swaps. The study revealed that rising real interest rates negatively affect stocks due to loss aversion and sentiment, while higher consumer confidence boosts the stock market through herding behavior and optimism. Market volatility was found to be negatively correlated with the S&P 500, influenced by risk aversion, recency bias, and herding behavior (Akin & Akin, 2024).

Amundi Research Center (2024) explores the impact of human-robot interactions on investors' behavior and risk-adjusted returns. The study highlights how these interactions can influence decision-making processes and lead to different investment outcomes compared to traditional human-only decision-making. This research underscores the importance of considering technological advancements in behavioral finance models (Amundi Research Center, 2024).

NBER (2024) reviews recent research on the formation of investors' subjective beliefs about future cash flows and prices. The study finds that return expectations of individual and professional investors, as captured in surveys, differ significantly from those implied by rational expectations models. This discrepancy highlights the role of behavioral factors in shaping market expectations and asset prices (NBER, 2024).

In 2024, Springer introduced an analytical framework that integrates theories from Information Economics, Behavioral Finance, and Market Efficiency with the latest FinTech innovations, such as blockchain, data analytics, and automated trading systems. The study explores how these technologies influence asset pricing and market behavior, suggesting that integrating FinTech innovations can enhance the understanding of market dynamics and investor behavior (Springer, 2024).

Studies in the Context of Nepal

Several studies have explored the impact of behavioral finance on investment decisions and asset pricing models in the Nepalese stock market.

In 2002, Poudel performed a risk-return assessment of commercial banks in Nepal, showing that the beta coefficient of individual stocks helps determine the minimum return rate investors need to compensate for systematic risk. However, the study also indicated that traditional CAPM might not fully apply to the Nepalese market because of its inefficiencies (Poudel, 2002).

Kiran (2010) concluded that the CAPM is not a reliable model for predicting common stock returns on the NEPSE for the total sample period of 1998 to 2008. The study indicated that there was a significant relationship between risk and return only in specific years, suggesting the need for alternative models that incorporate behavioral factors (Kiran, 2010).

Pokharel (2020) examined the influence of heuristic, prospect, market, and herding behaviors on investment performance in the Nepalese stock market. The study found that market factors significantly impact investment performance, while heuristic and herding behaviors do not show a significant relationship (Pokharel, 2020).

Gnawali (2021) investigated the effect of behavioral biases on individual investors' decision-making in the Nepalese stock market. The study used primary data from investors in broker houses and found that social interaction and regulatory policies significantly affect investment decisions, while psychological factors have a negative relationship (Gnawali, 2021).

Aryal (2021) studied the effect of behavioral biases on the investment performance of Nepali investors, focusing on overconfidence, loss aversion, familiarity, and herding mentality. The study found that only overconfidence bias significantly affected investment performance, while other biases were negatively but not significantly related to investment performance (Aryal, 2021).

Koirala (2021) proposed a modified asset-pricing model (MCAPM) that incorporates behavioral factors and provides a more comprehensive understanding of market dynamics in the Nepal Stock Exchange (NEPSE). The study found that traditional CAPM does not fully capture the risk-return relationship in the NEPSE, highlighting the importance of behavioral variables such as investor sentiment and trading behavior (Koirala, 2021).

In 2021, Poudel explored how cognitive biases influence investment decisions among Nepalese stock market investors. Using a self-administered questionnaire, the study identified key behavioral biases such as overconfidence, herd behavior, and loss aversion, and examined their impact on investment performance. The findings indicated that these biases significantly shape the decision-making process of individual investors in Nepal, often leading to less than optimal investment outcomes. This underscores the need to incorporate behavioral factors into asset pricing models to gain a better understanding of investor behavior in Nepal (Poudel, 2021).

Shrestha (2022) explored the connection between behavioral factors such as heuristics, prospect theory, herding behavior, and market variables, and the stock investment performance of individual investors in Nepal. The results showed that these behavioral factors significantly affect investment performance, aligning with the broader literature on behavioral finance (Shrestha, 2022).

In 2023, Dhakal and Lamsal investigated how cognitive biases affect the investment decisions of Nepalese stock market investors. They used a self-administered questionnaire to gather data from 234 respondents, focusing on six cognitive biases: overconfidence, herding, representativeness, anchoring, loss aversion, and confirmation biases. The study found that representativeness bias had the most significant impact on investment decision-making, with herding and anchoring biases also playing important roles.

Adhikari and Shrestha (2023) investigate the influence of investor sentiment on stock returns in the Nepal Stock Exchange. The study uses a sentiment index constructed from market data and news articles to analyze its impact on stock prices. The findings indicate that positive investor sentiment leads to higher stock returns, while negative sentiment results in lower returns. This highlights the importance of considering investor sentiment in asset pricing models in Nepal, as it significantly influences market movements (Adhikari & Shrestha, 2023).

Thapa and Poudel (2023) explore the relationship between market anomalies and behavioral factors in the Nepalese stock market. The study focuses on anomalies such as the January effect and momentum effect and investigates how behavioral biases like loss aversion and mental accounting contribute to these anomalies. The findings suggest that behavioral factors play a crucial role in explaining market anomalies in Nepal, providing a more comprehensive understanding of market behavior (Thapa & Poudel, 2023).

Chand (2024) examined the impact of behavioral biases such as loss aversion, herd behavior, anchoring, and risk perception on investment decisions in NEPSE. The study used descriptive and analytical research methods, surveying 384 NEPSE investors and analyzing the data with SPSS. The findings indicated that psychological biases significantly impact investment decisions, highlighting the need for broader market generalizability.

Aryal, Shrestha, Pradhan, Prajapati, & Basnet (2024) clarified how behavioral biases affect investor performance in NEPSE. The study employed a quantitative analysis using a purposive and causal research design with surveys of 124 respondents. The results showed that emotional biases like loss aversion and overconfidence significantly impact investor performance, while cognitive biases showed no significant effect.

In 2024, Gurung, Dahal, Ghimire, and Koirala investigated how behavioral biases affect investment decisions among Nepalese investors. Using a linear regression model and data from a structured questionnaire with 379 participants, the study found that overconfidence, anchoring, and regret aversion significantly influenced investment choices. Meanwhile, representative bias had little impact, and herding behavior showed no significant connection with investment decisions.

These studies underscore the relevance of behavioral finance in understanding asset pricing in emerging markets like Nepal. By integrating psychological biases and investor behavior into traditional models, researchers can develop more accurate and comprehensive frameworks for predicting stock returns and market dynamics.

Table 2.1 Summary of key aspects of research papers beyond the context of Nepal

S.N.	Author (s)	Objectives	Methodology	Finding
1	De Bondt & Thaler (1985)	To investigate if stock markets overreact to news.	Empirical analysis of stock returns.	Found that stock markets do overreact, leading to reversals.
2	Fama & French (1993)	To identify common risk factors in stock and bond returns.	Empirical analysis using regression models.	Identified size and value factors as significant.
3	Shefrin (2000)	To explore psychological factors influencing investor behavior.	Literature review and theoretical analysis.	Highlighted various behavioral biases affecting markets.
4	Shiller (2000)	To examine the role of investor sentiment in market bubbles.	Empirical analysis and case studies.	Demonstrated how sentiment drives market bubbles and crashes.
5	Barberis & Thaler (2003)	To provide an overview of behavioral finance concepts.	Literature review.	Summarized key behavioral finance theories and their implications.
6	Brown & Cliff (2005)	To investigate how investor sentiment influences asset prices.	Survey data and regression analysis.	Found a significant relationship between sentiment and market pricing errors.
7	Baker & Wurgler (2007)	To explore the impact of investor sentiment on stock prices.	Empirical analysis using sentiment indices.	Showed that sentiment significantly affects stock prices.
8	Johnston & Pennypacker (2009)	To discuss methods for behavioral research.	Theoretical and methodological review.	Provided strategies for effective behavioral research.
9	Amin & Pirzada (2014)	To apply behavioral finance concepts to the property market.	Literature review and theoretical analysis.	Highlighted the impact of psychological factors on property investment.
10	Huang et al. (2018)	To examine sentiment across different asset markets.	Empirical analysis using sentiment measures.	Found cross-market predictive linkages of sentiment.
11	Lekovic (2019)	To propose behavioral finance frameworks as alternatives to traditional models.	Theoretical and empirical analysis.	Suggested that behavioral models better capture real-world behavior.
12	Frydman et al. (2019)	To test investor behavior theories using neural data.	Experimental and empirical analysis.	Provided evidence of neural correlates of investor behavior.

S.N.	Author (s)	Objectives	Methodology	Finding
13	Nasiri et al. (2021)	To model asset pricing using behavioral variables.	Fama-Macbeth approach.	Found significant impact of behavioral variables on stock returns.
14	Frino et al. (2022)	To explore behavioral finance in emerging markets.	Empirical analysis.	Highlighted the importance of behavioral factors in emerging markets.
15	Boulu-Reshef et al. (2023)	To analyze investor sentiment experimentally.	Experimental analysis.	Demonstrated significant effects of sentiment on market behavior.
16	Padmavathy (2024)	To explore psychological factors influencing investment decisions.	Theoretical and empirical analysis.	Identified key psychological biases affecting market anomalies.
17	Gorzon, Bormann, & von Nitzsch (2024)	To measure behavioral bias factors in portfolio management.	Literature review and empirical analysis.	Identified 11 behavioral bias factors impacting portfolio performance.
18	Mangee (2023)	To examine the impact of Knightian uncertainty on stock prices.	Empirical analysis.	Found that uncertainty significantly affects stock price deviations.
19	Akin & Akin (2024)	To investigate the impacts of behavioral finance on US stock market volatility	Time-series analysis over a 10-year period	Rising real interest rates negatively affect stocks due to loss aversion and sentiment, while higher consumer confidence positively influences the stock market
20	Amundi Research Center (2024)	To explore the impact of human-robot interactions on investors' behavior and risk-adjusted returns	Analytical study	Human-robot interactions influence decision-making processes and lead to different investment outcomes
21	NBER (2024)	To review recent research on the formation of investors' subjective beliefs	Literature review	Return expectations of investors differ significantly from those implied by rational expectations models
22	Springer (2024)	To explore how FinTech innovations influence asset pricing and market	Analytical framework combining theories from	Integrating FinTech innovations can enhance the understanding of

S.N.	Author (s)	Objectives	Methodology	Finding
		behavior	Information Economics, Behavioral Finance, and Market Efficiency	market dynamics and investor behavior

This table summarizes the key aspects of each research paper, providing a clear overview of their contributions to the field of behavioral finance and asset pricing.

Table 2.2 Summary of key aspects research papers in context of Nepal

S.N.	Author (s)	Objectives	Methodology	Finding
1	Poudel (2002)	To assess the risk-return profile of commercial banks in Nepal.	Empirical analysis using stock trading data.	Traditional CAPM might not be fully applicable due to market inefficiencies.
2	Kiran (2010)	To evaluate the applicability of CAPM in NEPSE.	Empirical analysis using regression models.	CAPM does not provide a valid framework for predicting stock returns in NEPSE.
3	Pokharel (2020)	To examine the influence of behavioral factors on investment decisions in Nepal.	Survey and statistical analysis.	Market factors significantly impact investment performance, while heuristic and herding behaviors do not.
4	Gnawali (2021)	To investigate the effect of behavioral biases on individual investors' decision-making in Nepal.	Survey and statistical analysis.	Social interaction and regulatory policies significantly affect investment decisions.
5	Aryal (2021)	To study the impact of behavioral biases on the investment performance of Nepali investors.	Survey and statistical analysis.	Overconfidence bias significantly affects investment performance, while other biases have a negative but non-significant impact.
6	Koirala (2021)	To propose a modified asset-pricing model incorporating behavioral factors for NEPSE.	Empirical analysis using regression models.	Traditional CAPM does not fully capture the risk-return relationship in NEPSE.
7	Poudel (2021)	To examine the impact of cognitive biases on investment decisions among Nepalese stock market investors	Self-administered questionnaire survey	Cognitive biases such as overconfidence, herd behavior, and loss aversion significantly affect investment decisions
8	Shrestha (2022)	To examine the relationship between behavioral factors and stock investment performance in Nepal.	Survey and statistical analysis.	Behavioral factors significantly affect investment performance.
9	Adhikari & Shrestha (2023)	To investigate the influence of investor sentiment on stock returns in the Nepal	Sentiment index constructed from market data and news articles	Positive investor sentiment leads to higher stock returns, while negative sentiment

S.N.	Author (s)	Objectives	Methodology	Finding
		Stock Exchange		results in lower returns
10	Dhakal & Lamsal (2023)	To analyze the relationship between demographic factors and behavioral biases in share trading decisions in NEPSE.	Empirical analysis using survey data.	Found significant relationships between demographic factors and behavioral biases such as overconfidence, disposition effect, and herding bias.
11	Thapa & Poudel (2023)	To explore the relationship between market anomalies and behavioral factors in the Nepalese stock market	Empirical analysis focusing on anomalies like the January effect and momentum effect	Behavioral biases like loss aversion and mental accounting contribute to market anomalies
12	Chand (2024)	To examine the impact of behavioral biases such as loss aversion, herd behavior, anchoring, and risk perception on investment decisions in NEPSE.	Descriptive and analytical research using surveys of 384 NEPSE investors and SPSS for analysis.	Psychological biases significantly impact investment decisions, highlighting the need for broader market generalizability.
13	Aryal, Shrestha, Pradhan, Prajapati, & Basnet (2024)	To clarify how behavioral biases affect investor performance in NEPSE.	Quantitative analysis using a purposive and causal research design with surveys of 124 respondents.	Emotional biases like loss aversion and overconfidence significantly impact investor performance, while cognitive biases showed no significant effect.
14	Gurung, Dahal, Ghimire, & Koirala (2024)	To examine the influence of behavioral biases on investment decisions among Nepalese investors.	Empirical analysis using survey data.	Identified significant effects of overconfidence, representativeness, anchoring, regret aversion, and herding biases on investment decisions.

This table summarizes the key aspects of each research paper, providing a clear overview of their contributions to the understanding of behavioral finance and asset pricing in the context of Nepal.

2.3 Research Gap

Despite the growing body of literature on behavioral finance, there is still a significant gap in understanding how these behavioral biases specifically impact asset pricing models in the Nepalese stock market. Most studies have focused on individual investor behavior through surveys or interviews, without integrating these insights into asset pricing models.

For instance, studies by Pokharel (2020), Gnawali (2021), Aryal (2021), and Shrestha (2022) have primarily examined the influence of behavioral biases on investment decisions and performance using primary data from individual investors. While these studies provide valuable insights into how psychological factors affect investor behavior, they do not extend these findings to asset pricing models.

Additionally, research by Koirala (2021) and Kiran (2010) has highlighted the limitations of traditional CAPM in the Nepalese context, suggesting the need for models that incorporate behavioral factors. However, these studies have not fully explored the integration of behavioral biases into asset pricing models using historical trade data.

The studies highlight the importance of integrating behavioral finance insights into traditional models to better understand and predict market dynamics. By quantifying and measuring behavioral factors using historical trade data, researchers can develop more comprehensive asset pricing models that account for psychological biases and investor sentiment.

This research aims to fill this gap by developing a behavioral asset pricing model that incorporates trading volume, market sentiment, and momentum. By using historical trade data instead of individual investor surveys or interviews, this study seeks to provide a more comprehensive understanding of asset pricing in the Nepalese context. This approach will allow for the identification of behavioral factors directly from market data, offering a novel perspective on how psychological biases influence stock returns and market dynamics in Nepal

CHAPTER III

Research Methodology

This chapter outlines the research methodology employed in this study to investigate the impact of behavioral finance on asset pricing models, specially through the application of the Capital Asset Pricing Model (CAPM) on stocks listed on the Nepal Stock Exchange (NEPSE). By integrating behavioral finance theories with traditional asset pricing models, this study aims to develop a modified Capital Asset Pricing Model (CAPM) that incorporates psychological biases and investor sentiment. The extended model incorporates behavioral finance variables such as momentum, volatility, trading volume, and percentage changes in stock prices. The methodology includes the research design, population and sample, sources of data, data collection and processing procedures, variable construction, and tools and analysis techniques used to examine the influence of these factors on stock returns.

3.1 Research Design

This study employs a quantitative approach using secondary data to investigate the impact of behavioral finance on asset pricing models in the Nepal Stock Exchange (NEPSE). The research focuses on listed equities, analyzing historical trade data to identify behavioral factors influencing stock returns. The study integrates behavioral finance theories with traditional asset pricing models to develop a modified Capital Asset Pricing Model (CAPM) that incorporates psychological biases and investor sentiment. This study extends the traditional CAPM model by incorporating behavioral factors, utilizing statistical tools and financial modeling to assess the relationships between stock returns and variables derived from behavioral finance theories.

The research design for this study is a quantitative descriptive design. This approach is chosen to systematically describe the characteristics of the variables of interest, which include stock prices, trading volumes, and financial ratios of 30 selected companies listed on the Nepal Stock Exchange (NEPSE). The study aims to analyze the historical performance of these companies' stocks using the Capital Asset Pricing Model (CAPM) and other financial metrics over the period from 2017 to 2022. By employing a quantitative descriptive design, the research can provide a detailed and objective analysis of the stocks' behavior over time, allowing for the identification of trends, patterns, and relationships among the variables.

Conceptual Framework:

The conceptual framework for this study is based on the integration of traditional finance theories and behavioral finance insights. The framework illustrates the relationships between traditional finance factors (risk-free rate, beta, market return) and behavioral finance factors (momentum, volatility, trading volume) in influencing stock returns. This framework is adapted from the works of Barberis and Thaler (2003) and Fama and French (1993), who have extensively studied the impact of psychological factors on asset pricing.

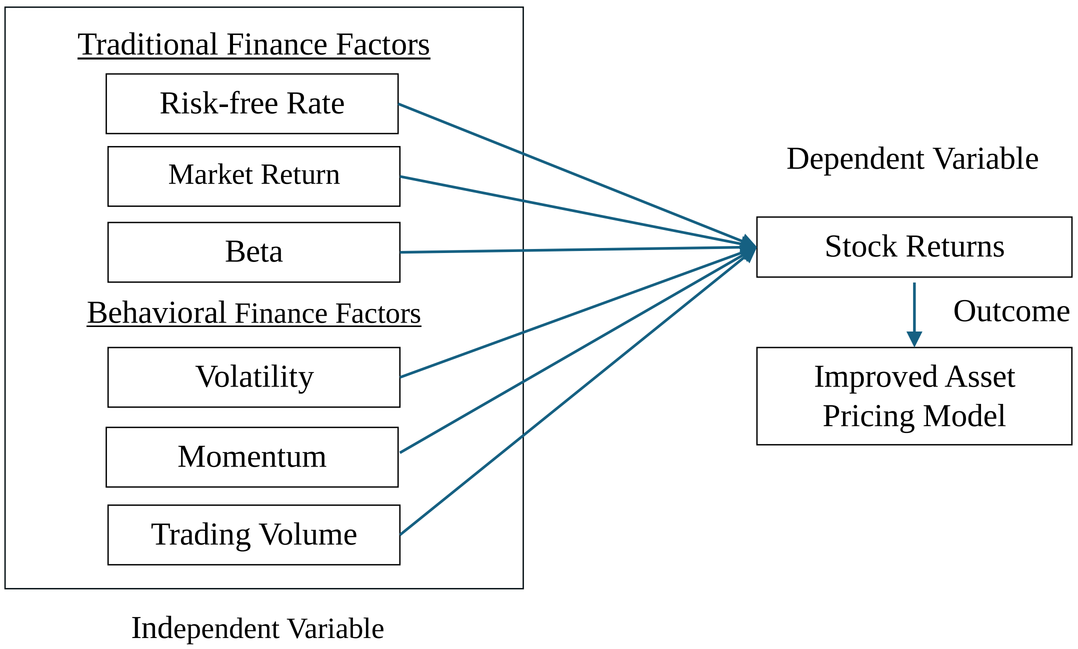

Figure 3.1: Conceptual Framework

(Source: Adapted from the works of Barberis and Thaler (2003) and Fama and French (1993))

This diagram visually represents the relationships between traditional finance factors, behavioral finance factors, and stock returns. It highlights how these variables interact to impact asset pricing in the Nepalese stock market, ultimately leading to improved asset pricing models. This framework helps in understanding the influence of both traditional and behavioral factors on asset pricing, providing a comprehensive approach to analyzing market dynamics.

3.2 Population and Sample

Population: The population for this study consists of all 243 companies listed on the Nepal Stock Exchange (NEPSE).

Sample: A sample of 30 actively traded companies from various sectors is selected based on liquidity and data availability during the study period of 2017–2022. The selection ensures that the companies have sufficient trading volume and represent different industries, thereby providing a comprehensive view of the Nepalese stock market. The sampling method employed is stratified random sampling, where the companies are first divided into different strata based on industry sectors, and then a random sample is taken from each stratum. This method ensures that the sample is representative of the entire population and captures the diversity of the market. The rationale behind using this method is to ensure that all industry sectors are adequately represented in the sample, providing a comprehensive overview of the stock market performance. To ensure a representative sample, the study merges related sectors and selects a proportional sample from each merged sector. A sample size of 30 has been chosen based on practical and statistical considerations.

i) Practical Considerations

Manageability: A sample size of 30 is manageable in terms of data collection, analysis, and interpretation, especially for a Master's thesis.

Resource Constraints: Limited time, budget, and resources often necessitate a smaller sample size.

ii) Statistical Considerations

Central Limit Theorem: According to this theorem, for sample sizes of 30 or more, the sampling distribution of the sample mean tends to be normally distributed, regardless of the population's distribution. This makes statistical analysis more robust and reliable.

Sufficient Representation: A sample size of 30 can provide a reasonable representation of the population, especially when using stratified sampling to ensure all sectors are included.

By considering both practical and statistical factors, the chosen sample size of 30 ensures that the study is both feasible and statistically sound, providing a comprehensive understanding of the impact of behavioral finance on asset pricing models in the Nepal Stock Exchange (NEPSE).

Table 3.1: Merged Sectors and Sample Size

Sector	**Number of Listed Companies**	**Merged Sector**	**Sample Size**
Commercial Banks	19	Banks	6
Development Banks	16		
Finance	15		
Life Insurance	12	Insurance	3
Non-Life Insurance	12		
Microfinance	48	Microfinance	6
Hydro Power	91	Hydro Power	11
Hotels and Tourism	6	Others	4
Investment	7		
Manufacturing and Processing	9		
Others	6		
Tradings	2		
Total	**243**		**30**

Rationale: Stratified random sampling is chosen to ensure that each sector is proportionally represented, providing a comprehensive understanding of the impact of behavioral finance across different sectors in the NEPSE.

Table 3.2 Selected Companies for the Study

Sector	**Sample Size**	**Selected Companies**
Banks	6	Himalayan Bank Limited (HBL) Nabil Bank Limited (NABIL) Agricultural Development Bank Limited (ADBL) Jyoti Bikas Bank Limited (JBBL) Muktinath Bikas Bank Ltd. (MNBBL) Nepal Finance Ltd. (NFS)
Insurance	3	Nepal Life Insurance Co. Ltd. (NLIC) Nepal Insurance Co. Ltd. (NICL) Neco Insurance Limited (NIL)
Microfinance	6	Nirdhan Utthan Laghubitta Bittiya Sanstha Limited (NUBL) Chhimek Laghubitta Bittiya Sanstha Limited (CBBL) Deprosc Laghubitta Bittiya Sanstha Limited (DDBL) Swabalamban Laghubitta Bittiya Sanstha Limited (SWBBL) First Micro Finance Laghubitta Bittiya Sanstha Limited (FMDBL) Sana Kisan Bikas Laghubitta Bittiya Sanstha Limited (SKBBL)
Hydro Power	11	Butwal Power Company Limited (BPCL) Chilime Hydropower Company Limited (CHCL) Arun Valley Hydropower Development Co. Ltd. (AHPC) Sanima Mai Hydropower Ltd. (SHPC) Api Power Company Ltd. (API) Kalika Power Company Ltd. (KPCL) Radhi Bidyut Company Ltd. (RADHI) Panchakanya Mai Hydropower Ltd. (PMHPL) Chhyangdi Hydropower Ltd. (CHL) Arun Kabeli Power Ltd. (AKPL) Ngadi Group Power Ltd. (NGPL)

Others	4	Nepal Doorsanchar Company Limited (NTC) Himalayan Distillery Limited (HDL) Citizen Investment Trust (CIT) Salt Trading Corporation (STC)

3.3 Sources of Data

The study utilizes secondary data sources, primarily historical trade data from the NEPSE. Additional data sources include financial statements, market reports, and investor sentiment indices. Financial information platforms as well as data from Nepal Rastra Bank, are also used to gather comprehensive data on stock trade, analysis, and market news.

The primary sources of data for this research are:

Historical stock price data of the 30 selected companies, including daily maximum, minimum, and closing prices, as well as trading volumes and turnover, extracted from the NEPSE database and other financial data providers.

Risk-free rate data from the Nepal Rastra Bank, which includes annualized rates for different durations of treasury bills. This data is crucial for calculating the expected returns using CAPM.

Behavioral factors data modeled from historical trade data, such as trading volume, price momentum, and volatility, to capture the psychological and emotional aspects influencing investor behavior.

3.4 Data Collection

Data Type:

This study uses secondary data, including stock prices, trading volumes, and financial metrics from publicly available sources such as NEPSE's official records and financial reports of the listed companies. Daily data is collected to ensure precise calculations of returns, volatility, and behavioral factors. The following data sets are gathered:

- Daily stock prices (maximum, minimum, and closing prices) for the sample companies.

- Trading volumes to capture market activity and liquidity.
- Risk-free rate data (annualized rates of treasury bills) for the CAPM analysis.
- Market index returns to represent the NEPSE market portfolio.
- Behavioral factors derived from price momentum, volatility, and percentage changes.

Time Frame

The study covers a 6-year period from 2017 to 2022, focusing on daily data to capture short-term market fluctuations and investor behavior.

Data Collection Procedure

The historical trading data of the selected companies is collected from the NEPSE database and the financial information platforms. Other relevant information including Risk-free rate are collected from Nepal Rasta Bank. The data collection procedure involves the following steps:

- **Data Extraction:** Extracting daily stock prices, trading volumes, turnover, risk-free rates, and behavioral factors from the NEPSE database, Nepal Rastra Bank, financial information platforms, and other relevant sources. This step ensures that all relevant data is gathered for analysis.
- **Data Cleaning:** Ensuring the data is free from errors, missing values, and inconsistencies. This involves checking for any anomalies or outliers that could skew the results.
- **Data Organization:** Structuring the data in a format suitable for analysis, including organizing it by date and ensuring all relevant variables are included. This step involves creating a comprehensive dataset that integrates all the necessary information for analysis.

3.5 Data Processing Procedure

The data processing procedure includes the following steps:

Data Validation: Checking the accuracy and completeness of the data. This involves verifying that the data entries are correct and consistent with the original sources.

Data Transformation: Converting raw data into a format suitable for analysis, such as calculating daily returns and percentage changes. This step involves creating new variables that capture the essential characteristics of the stocks' performance.

Data Integration: Combining data from different sources if necessary to create a comprehensive dataset. This ensures that all relevant information is available for analysis, providing a holistic view of the stocks' performance.

3.6 Variables and Measurements

The variables used in the analysis can be categorized into dependent and independent variables, which are essential for performing CAPM and behavioral finance analyses.

3.6.1 Dependent Variables*:*

Stock Returns ($\boldsymbol{R_i}$): Daily returns calculated as the percentage change in closing prices. This measures the profitability of the stocks over time.

$$Return_t = \frac{Closing\ Price_t - Closing\ Price_{t-1}}{Closing\ Price_{t-1}} \times 100$$

where, $Closing\ Price_t$ is the closing price at time t.

3.6.2 Independent Variables:

<u>**Traditional Finance Factors:**</u>

Risk-Free Rate ($\boldsymbol{R_f}$): The **Risk-Free Rate ($\boldsymbol{R_f}$)** represents the return an investor can expect from an investment with zero risk, typically based on government-issued securities like treasury bills. In this study, the 91-day Treasury Bills Rate is used to approximate the risk-free rate, as provided by the Nepal Rastra Bank (the Central Bank of Nepal). This rate is annualized and derived from the Weighted Average Treasury Bills Rate for each fiscal year.

Since the analysis requires daily data, the annualized rate is converted into a daily risk-free rate using the following formula:

$$Rf_{daily} = \left(1 + \frac{Rf_{annual}}{100}\right)^{\frac{1}{365}} - 1$$

where,

- Rf_{annual} is the annualized percentage rate of the 91-day treasury bill for a particular fiscal year (e.g., 4.22% for 2017/18).
- The exponent $\frac{1}{365}$ converts the annual rate to a daily rate by assuming there are 365 days in a year.

The risk-free rate is a critical component in asset pricing models, including the Capital Asset Pricing Model (CAPM), where it serves as a benchmark for expected returns on risky assets. The difference between the expected return on a stock and the risk-free rate, known as the risk premium, helps assess the additional compensation investors demand for taking on the risk of holding a stock instead of a risk-free asset.

The risk-free rate used in this analysis is derived from the Weighted Average Treasury Bills Rate (91-day). The annualized rates, which vary by fiscal year, reflect the prevailing short-term, low-risk interest rates during those periods. For accurate modeling, these annualized rates are converted into daily rates, which are more appropriate for the daily stock data used in this study.

The annualized rates for each fiscal year from 1988/89 to 2022/23 are summarized in **Table 3.3**, and they form the basis for calculating the daily risk-free rates used in the CAPM and other asset pricing models within this study. These rates are sourced from the Nepal Rastra Bank (the Central Bank of Nepal).

Table 3.3: Weighted Average Treasury Bills Rate (91–day) - Annualised Percent

Fiscal year	**Annual**		Fiscal year	**Annual**		Fiscal year	**Annual**		Fiscal year	**Annual**
1988/89	**5.24**		1998/99	**2.33**		2008/09	**5.83**		2018/19	**3.20**
1989/90	**6.20**		1999/00	**4.66**		2009/10	**6.50**		2019/20	**2.69**
1990/91	**8.18**		2000/01	**4.96**		2010/11	**7.41**		2020/21	**2.19**
1991/92	**9.24**		2001/02	**4.71**		2011/12	**1.31**		2021/22	**6.67**
1992/93	**11.34**		2002/03	**3.48**		2012/13	**1.74**		2022/23	**9.51**
1993/94	**6.50**		2003/04	**2.93**		2013/14	**0.13**			
1994/95	**7.35**		2004/05	**2.46**		2014/15	**0.43**			
1995/96	**10.93**		2005/06	**2.84**		2015/16	**0.79**			
1996/97	**10.22**		2006/07	**2.42**		2016/17	**1.45**			
1997/98	**3.52**		2007/08	**4.22**		2017/18	**4.48**			

Market Return ($\boldsymbol{R_m}$): The Market Return (R_m) represents the return on the overall stock market and serves as a benchmark for the performance of individual stocks or portfolios. In this study, the NEPSE index, which tracks the performance of all the listed stocks in the Nepal Stock Exchange, is used as a proxy for the market return.

The NEPSE index captures the value-weighted average price movements of all listed stocks, reflecting the general trend of the Nepalese stock market. By using the NEPSE index as a proxy for market return, we can evaluate how individual stocks perform relative to the broader market. The return on the overall market, represented by the NEPSE index.

To calculate the daily market return, the percentage change in the NEPSE index is computed as follows:

$$R_{m,t} = \frac{NEPSE\ Index_t - NEPSE\ Index_{t-1}}{NEPSE\ Index_{t-1}} \times 100$$

where,

- $R_{m,t}$ is the daily market return at time t.
- $NEPSE\ Index_t$ is the value of the NEPSE index at time t.
- $NEPSE\ Index_{t-1}$ is the value of the NEPSE index at time $t-1$.

The market return is crucial for models like the Capital Asset Pricing Model (CAPM), where it is compared with the risk-free rate to determine the expected return on a stock based on its beta (systematic risk relative to the market).

Beta: Beta is a measure of a stock's systematic risk in comparison to the overall market. It is calculated through regression analysis using the following formula:

$$\beta = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

where:

- R_i is the return on the individual stock.
- R_m is the return on the market.

- $Cov(R_i, R_m)$ is the covariance between the stock and market returns.
- $Var(R_m)$ is the variance of the market returns.

Behavioral Finance Factors:

Volatility: The standard deviation of daily returns, indicating the risk or variability in stock returns.

$$Volatility = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(Return_t - \overline{Return})^2}$$

where, N is the number of trading days, and $\overline{Return}$ is the average daily return.

Momentum: Rate of change in stock prices over a specified period. This variable captures the trend and potential future price movement of the stocks.

$$Momentum_t = \frac{Closing\ Price_t - Closing\ Price_{t-n}}{Closing\ Price_{t-n}} \times 100$$

where, n is the number of periods (e.g. days) between price comparisons.

Trading Volume: Represents the total number of shares traded in a given period. This variable indicates liquidity and investor interest in the stocks.

$$Trading\ Volume = \sum_{t=1}^{N} Volume_t$$

where N is the number of days in the period.

Supporting Variables (for Calculations):

Stock Prices: Maximum, minimum, and closing prices. These variables provide the basis for calculating returns, momentum, volatility, and other financial metrics.

Turnover: Total value of shares traded, reflecting market activity. This variable reflects the overall market activity and the financial significance of the trades.

$$Turnover = \sum_{t=1}^{N} (Volume_t \times Price_t)$$

This reflects the market activity and liquidity.

3.6.3 Behavioral Factors:

Behavioral factors modeled from historical trade data include variables like trading volume, price momentum, and volatility, which act as proxies for investor behavior and psychology. These variables capture the emotional and psychological aspects that can impact stock prices and trading volumes.

The following behavioral finance factors are modeled using daily stock trading data to capture investor psychology:

- **Momentum**: Represents the continuation of stock price trends due to investor herding.
- **Volatility**: Reflects market uncertainty and investor reactions to risk.
- **Trading Volume**: Reflects market liquidity and investor enthusiasm.

3.7 Model Estimation

The traditional Capital Asset Pricing Model (CAPM) explains the expected return of a security based on its systematic risk relative to the overall market. However, it assumes that markets are efficient and that investors behave rationally. Behavioral finance challenges these assumptions by highlighting the role of cognitive biases, emotions, and irrational behaviors in investment decisions. This study proposes an extended CAPM that incorporates behavioral finance factors to examine how these factors influence asset pricing.

This extended model integrates behavioral variables such as **momentum**, **volatility**, **trading volume**, and **percentage change**, alongside traditional market-based variables, to capture investor sentiment and psychology that impact stock prices.

Incorporating behavioral factors into the traditional CAPM involves expanding the equation to include variables like momentum, volatility, sentiment, and trading volume. These behavioral factors reflect investor sentiment and market psychology, which are critical in asset pricing.

Traditional CAPM Model:

The traditional CAPM formula estimates the expected return of a stock based on its systematic risk (beta):

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

where:

- $E(R_i)$ is the expected return of stock i,
- R_f is the risk-free rate,
- β_i is the stock's beta, measuring its systematic risk relative to the market,
- $E(R_m)$ is the expected return of the market.

Extended Behavioral CAPM Model:

The traditional CAPM equation is expanded to account for the potential effects of investor sentiment and irrational behaviors on stock prices. The extended CAPM model incorporates behavioral finance factors:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) + \gamma_1 \cdot Momentum + \gamma_2 \cdot Volatility + \gamma_3 \cdot TradingVolume + \epsilon$$

Where:

- $E(R_i)$ is the expected return of stock i,
- R_f is the risk-free rate,
- β_i is the asset's beta, measuring its systematic risk relative to the market,

- $E(R_m)$ is the expected return of the market,
- $\gamma_1, \gamma_2, \gamma_3$ are the coefficients capturing the influence of behavioral factors,
- ϵ is the error term.

3.8 Data Analysis Tools and Techniques

Descriptive Statistics: Mean, median, standard deviation, and variance are used to summarize the stock performance, market behavior, and the distribution of behavioral factors.

Regression Analysis: Multiple regression is used to estimate the impact of traditional CAPM variables and behavioral factors on stock returns. The regression equation is:

$$R_i = \alpha + \beta_i(R_m - R_f) + \gamma_1 \cdot Momentum + \gamma_2 \cdot Volatility + \gamma_3 \cdot TradingVolume + \epsilon$$

Ordinary least squares (OLS) is used to estimate the coefficients $\gamma_1, \gamma_2, \gamma_3$ reflecting the influence of behavioral factors.

CAPM Analysis: The expected return is calculated using CAPM, comparing the results of the traditional and behavioral models to determine the explanatory power of behavioral factors.

Time Series Analysis: Used to analyze stock price trends, volatility, and momentum over time. This involves examining the data for seasonal effects, trends, and cyclical patterns.

Statistical Testing: T-tests are conducted to assess the significance of the behavioral factors, while R-squared and adjusted R-squared values are used to evaluate the model's fit.

Software Packages: Microsoft Excel and Python programming for data organization, cleaning, and calculation of financial metrics like stock returns, volatility, and momentum as well as for advanced statistical analysis, including regression, CAPM calculations and time-series modeling. The tool provides the necessary functionality for performing complex analyses and visualizing the results.

CHAPTER IV

Results and Discussion

4.1 Data Presentation and Analysis

This section provides a detailed comparative analysis of traditional and behavioral Capital Asset Pricing Models (CAPM) to examine the influence of behavioral factors on asset pricing. The extended CAPM model, which includes factors such as momentum, volatility, and trading volume, offers insights into how investor psychology affects stock performance in the Nepal Stock Exchange (NEPSE). Various visualizations illustrate key relationships and trends, enhancing the comparative analysis of traditional and behavioral models.

Table 4.1: Traditional CAPM Regression Results

	Intercept	Market Return Coefficient	R-squared	P-value (Intercept)	P-value (Market Return)
ADBL	-0.00043	-0.0541	0.001937	0.43915	0.135464
AHPC	0.000657	-0.27695	0.016307	0.497483	1.43E-05
AKPL	0.0004	-0.21906	0.01036	0.688757	0.000813
API	0.000177	-0.24768	0.012511	0.85767	0.000143
BPCL	-0.00027	-0.10844	0.005332	0.683409	0.013374
CBBL	0.000291	-0.06159	0.001586	0.677051	0.177007
CHCL	-0.00033	-0.14192	0.009296	0.61882	0.001045
CHL	0.000699	-0.06074	0.000785	0.511345	0.382023
CIT	-0.00021	-0.04486	0.00062	0.792195	0.399349
DDBL	7.07E-05	-0.08457	0.001828	0.936859	0.147366
FMDBL	0.000208	-0.19898	0.00963	0.819339	0.000853
HBL	-0.00061	0.018861	0.000171	0.374238	0.6836
HDL	0.002377	-0.13134	0.002979	0.052273	0.088478
JBBL	0.000523	-0.12098	0.004333	0.528013	0.027122
KPCL	0.002235	-0.21219	0.010102	0.088282	0.006142
MNBBL	-0.00019	-0.10654	0.004145	0.794678	0.030391
NABIL	-0.0004	0.052441	0.001416	0.527523	0.201867
NFS	0.001656	-0.14927	0.003357	0.446246	0.194497
NGPL	0.00046	-0.28937	0.014074	0.676285	5.93E-05
NICL	-0.00011	-0.20261	0.009026	0.910384	0.001282
NIL	0.000169	-0.16145	0.008015	0.834375	0.002355
NLIC	-0.00113	-0.0824	0.002513	0.127155	0.088988
NTC	0.000202	-0.07682	0.002924	0.752324	0.066529
NUBL	7.63E-05	-0.03852	0.000439	0.926735	0.479576
PMHPL	0.0017	-0.07913	0.001243	0.22083	0.335641
RADHI	0.000689	-0.19919	0.005751	0.61508	0.025212
SHPC	-0.00054	-0.17019	0.007588	0.535794	0.003125
SKBBL	0.000208	-0.15704	0.009714	0.776661	0.000983
STC	0.003788	-0.17769	0.007463	0.018254	0.040811
SWBBL	0.000275	-0.16452	0.008147	0.722791	0.002285

Table 4.2: Behavioral CAPM Regression Results

	Intercept	Market Return Coefficient	Momentum Coefficient	Volatility Coefficient	Trading Volume Coefficient	R-squared	P-value (Intercept)	P-value (Market Return)	P-value (Momentum)	P-value (Volatility)	P-value (Trading Volume)
ADBL	-0.00041	-0.00078	0.002139	-0.00145	0.002279	0.045595	0.453085	0.14851	0.000384	0.009226	0.00017
AHPC	0.000756	-0.00423	0.004961	-0.00251	0.004467	0.066844	0.42309	8.17E-06	5.75E-06	0.018968	0.000161
AKPL	0.000451	-0.00325	0.003647	-0.00113	0.004845	0.060242	0.643363	0.000883	0.003989	0.277738	0.00013
API	0.000267	-0.00361	0.004756	-0.00209	0.005191	0.065978	0.780885	0.000186	7.72E-06	0.047575	4.55E-06
BPCL	-0.00023	-0.00155	0.003297	-0.00141	0.003639	0.068519	0.71735	0.016862	2.96E-06	0.032265	3.61E-07
CBBL	0.000316	-0.00087	0.004165	-0.00085	0.002203	0.047848	0.643339	0.200282	3.59E-09	0.216368	0.001735
CHCL	-0.00027	-0.00195	0.002796	-0.00139	0.003395	0.056862	0.673164	0.002555	4.89E-05	0.036571	1.09E-06
CHL	0.000702	-0.00085	0.004795	-0.00324	0.0066	0.070836	0.494386	0.407721	0.00012	0.008346	1.42E-06
CIT	-0.0002	-0.00056	0.003579	8.10E-05	0.002323	0.029702	0.806112	0.48597	1.75E-05	0.923076	0.00719
DDBL	0.000105	-0.00122	0.004021	0.0003	0.001742	0.028054	0.904906	0.168157	4.92E-05	0.745603	0.072918
FMDBL	0.000288	-0.00282	0.003124	-0.0021	0.006714	0.081377	0.743009	0.001341	0.001282	0.019694	1.05E-11
HBL	-0.00063	0.000216	0.003478	-0.00092	0.001521	0.041542	0.35218	0.749996	6.73E-06	0.229954	0.03378
HDL	0.002408	-0.00158	0.00686	-0.00118	0.003917	0.053053	0.044024	0.188051	3.82E-08	0.331235	0.001507
JBBL	0.000552	-0.00175	0.002327	-0.00278	0.005258	0.065398	0.492086	0.029706	0.019583	0.00125	3.76E-07
KPCL	0.002355	-0.00311	0.001999	-0.00335	0.010163	0.096724	0.060524	0.013467	0.1967	0.014992	2.66E-10
MNBBL	-0.00016	-0.00161	0.002204	-0.00162	0.004092	0.054106	0.822662	0.02709	0.012021	0.040796	3.27E-06
NABIL	-0.00042	0.000782	0.003312	-0.00109	0.000768	0.035898	0.49837	0.206789	2.54E-06	0.105023	0.277278
NFS	0.001699	-0.00258	0.006514	-0.00372	0.00933	0.080973	0.416927	0.219745	0.004136	0.078305	3.95E-05
NGPL	0.000588	-0.00416	0.003931	-0.00381	0.007283	0.072614	0.583029	0.00011	0.001703	0.00172	1.94E-07
NICL	-3.10E-05	-0.00289	0.005365	-0.00024	0.003166	0.058077	0.973281	0.002092	1.92E-07	0.800757	0.002126
NIL	0.000235	-0.00199	0.004292	-0.00028	0.003283	0.063814	0.765112	0.011751	3.06E-06	0.726766	0.000317
NLIC	-0.0011	-0.001	0.005209	-0.00164	0.000255	0.053325	0.129084	0.170024	8.30E-10	0.034446	0.769907
NTC	0.000233	-0.00069	0.001979	-0.00344	0.006024	0.089653	0.703017	0.258926	0.00599	1.41E-06	2.84E-13
NUBL	8.88E-05	-0.00033	0.004536	-0.00058	0.00343	0.049044	0.912691	0.687317	1.12E-07	0.491982	3.56E-05
PMHPL	0.001746	-0.00136	0.005473	-0.0044	0.008151	0.074961	0.192175	0.30984	0.000461	0.004532	5.86E-07
RADHI	0.000727	-0.0028	0.009491	-0.00107	-0.00249	0.057627	0.586318	0.036821	7.19E-11	0.460932	0.10433
SHPC	-0.00048	-0.00233	0.004918	-0.00062	0.002781	0.057006	0.575729	0.006524	4.61E-07	0.489755	0.003491
SKBBL	0.000272	-0.00228	0.004384	-0.00116	0.001686	0.053148	0.704129	0.001507	5.84E-09	0.109635	0.025531
STC	0.003921	-0.0026	0.012415	-0.00387	0.005361	0.120338	0.009615	0.086682	6.72E-12	0.029988	0.000578
SWBBL	0.000362	-0.00203	0.004164	-0.00096	0.002743	0.053334	0.633461	0.00764	2.78E-07	0.21656	0.000777

Table 4.3: Comparison of R-squared Values

	Traditional CAPM R-squared	Behavioral CAPM R-squared
ADBL	0.001937	0.045595
AHPC	0.016307	0.066844
AKPL	0.01036	0.060242
API	0.012511	0.065978
BPCL	0.005332	0.068519
CBBL	0.001586	0.047848
CHCL	0.009296	0.056862
CHL	0.000785	0.070836
CIT	0.00062	0.029702
DDBL	0.001828	0.028054
FMDBL	0.00963	0.081377
HBL	0.000171	0.041542
HDL	0.002979	0.053053
JBBL	0.004333	0.065398
KPCL	0.010102	0.096724
MNBBL	0.004145	0.054106
NABIL	0.001416	0.035898
NFS	0.003357	0.080973
NGPL	0.014074	0.072614
NICL	0.009026	0.058077
NIL	0.008015	0.063814
NLIC	0.002513	0.053325
NTC	0.002924	0.089653
NUBL	0.000439	0.049044
PMHPL	0.001243	0.074961
RADHI	0.005751	0.057627
SHPC	0.007588	0.057006
SKBBL	0.009714	0.053148
STC	0.007463	0.120338
SWBBL	0.008147	0.053334

In the traditional CAPM results (Table 4.1), the Market Return coefficient varies widely across stocks, and R-squared values are low for most securities, suggesting that traditional CAPM alone accounts for a limited portion of return variability. Some stocks, such as AHPC, AKPL, and API, show negative and statistically significant market return coefficients, indicating an inverse relationship with market movements. With most R-squared values ranging between 0.01 and 0.02, the traditional CAPM appears insufficient in capturing other influential factors that impact stock returns on NEPSE. The R-squared values indicate the proportion of variance in the stock returns explained by the market returns. For example, ADBL shows a low R-squared of 0.001937, suggesting that market returns explain very little of ADBL's return variability, while stocks like AHPC (R-squared of 0.016307) provide a slightly better fit.

The Behavioral CAPM model (Table 4.2), which integrates behavioral variables, shows an increase in R-squared values across most stocks, with values generally between 0.04 and 0.12. This improvement in explanatory power implies that behavioral factors contribute meaningfully to understanding stock returns. Momentum and trading volume emerge as significant determinants for numerous stocks, emphasizing the role of investor sentiment and volume-based effects on returns. For example, AHPC and NGPL experience marked increases in R-squared values, which supports the hypothesis that behavioral elements—reflecting psychological influences on pricing—significantly impact stock returns. The addition of behavioral factors shows a significant increase in R-squared values across most stocks compared to traditional CAPM, indicating that these factors better explain stock returns. For instance, ADBL has an R-squared of 0.045595, which is notably higher than in the traditional CAPM. The p-values for various coefficients indicate the statistical significance of the behavioral factors.

In particular, high momentum and trading volume are influential for stocks like STC, API, and AHPC, demonstrating that these behavioral factors play a crucial role in the Nepalese market. Volatility also shows strong relevance, with stocks such as BPCL, CIT, and RADHI reflecting positive coefficients for this factor, indicating heightened investor sensitivity to market uncertainty and volatility in asset pricing. This comparative analysis of traditional versus behavioral CAPM thus highlights the added depth behavioral finance provides in explaining asset pricing dynamics, especially in emerging markets where investor psychology can substantially impact market behavior.

The R-squared comparison (Table 4.3) between the traditional CAPM and the behavioral CAPM model tells notable improvements in explanatory power when behavioral factors are incorporated, emphasizing the role of investor psychology in driving stock returns on the Nepal Stock Exchange (NEPSE). For instance, stocks such as STC, KPCL, and NTC show substantial gains in R-squared values with the behavioral CAPM. STC's traditional R-squared of 0.007463 rises sharply to 0.120338 in the behavioral model, indicating that investor-driven factors like momentum and market sentiment play a significant role in explaining its returns. Similarly, KPCL and NTC see substantial increases from 0.010102 to 0.096724 and from 0.002924 to

0.089653, respectively, further underscoring the effectiveness of behavioral CAPM in capturing factors relevant to these stocks' return behaviors.

Other stocks, including ADBL and API, also display moderate gains in R-squared values with the behavioral CAPM, suggesting that these stocks' returns are influenced by behavioral factors such as trading volume and volatility. ADBL's R-squared, for example, rises from 0.001937 to 0.045595, and API from 0.012511 to 0.065978, indicating the impact of behavioral elements on these companies' return variations. Across the board, the behavioral CAPM model demonstrates greater accuracy in capturing the complexities of stock returns, providing a more nuanced understanding of NEPSE's dynamics. This pattern of improvement validates the importance of incorporating behavioral finance principles to explain return variability in emerging markets like Nepal, where investor psychology and market sentiment are particularly influential.

The increase in R-squared values when transitioning from Traditional CAPM to Behavioral CAPM suggests that including behavioral factors significantly enhances the model's explanatory power. For instance, stock STC shows a dramatic rise in R-squared from 0.007463 in Traditional CAPM to 0.120338 in Behavioral CAPM, indicating that behavioral factors have a substantial impact on its returns.

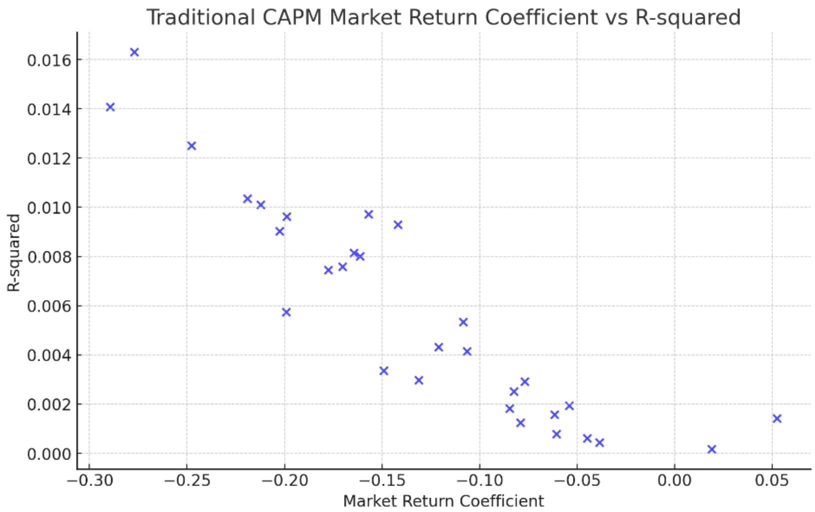

Figure 4.1: Traditional CAPM Market Return Coefficient vs R-squared

In the scatter plot of the Traditional CAPM Market Return Coefficient versus R-squared (*Figure 4.1*), most stocks have negative market return coefficients and relatively low R-squared values, suggesting limited explanatory power for the model in capturing the variation in stock returns. Only a few data points deviate from this trend, indicating that traditional CAPM may not fully account for the risk-return relationship in these stocks, possibly underscoring the potential need for additional factors beyond the market return to explain stock performance effectively.

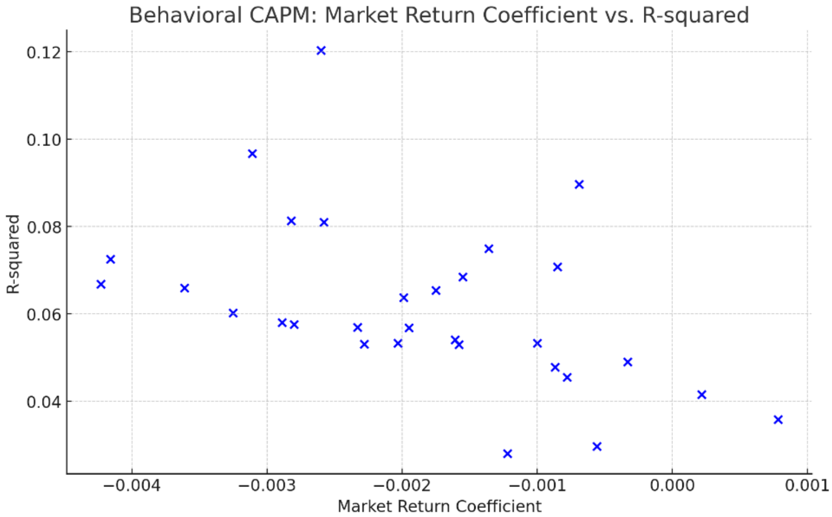

Figure 4.2: Behavioral CAPM Market Return Coefficient vs R-squared

In the scatter plot for the Behavioral CAPM, there is a more concentrated spread of data points at higher R-squared values compared to the Traditional CAPM. This suggests that behavioral factors may account for a larger portion of the variation in stock returns, as indicated by higher R-squared values across most data points. This indicates that the Behavioral CAPM might better capture market nuances and investor psychology than the Traditional CAPM, which has a generally lower explanatory power. However, the market return coefficients remain relatively low, signifying only minor sensitivity to market-wide factors when behavioral adjustments are considered.

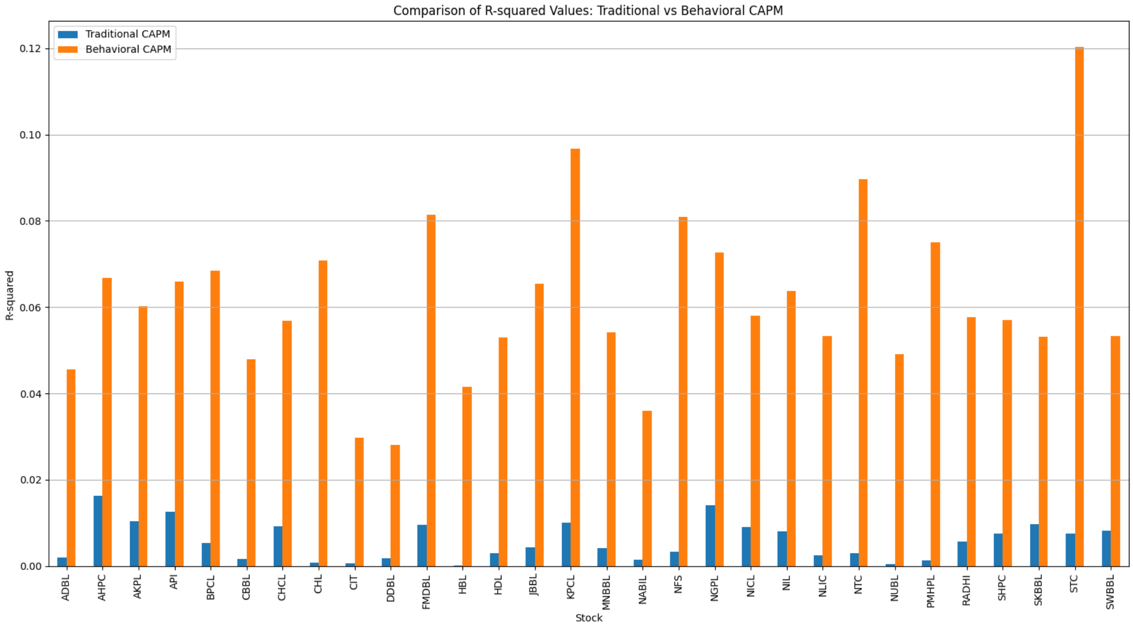

Figure 4.3: Comparison of R-squared Values – Traditional vs Behavioral CAPM

The comparison chart reveals that Behavioral CAPM consistently outperforms Traditional CAPM in terms of R-squared values, indicating a stronger model fit across all companies. Notably, certain stocks such as KPCL, STC, and NTC demonstrate this difference prominently. For instance, STC exhibits the highest R-squared value under Behavioral CAPM at 0.120338, compared to a mere 0.007463 under Traditional CAPM, suggesting a significant increase in explanatory power when behavioral factors are included. Similarly, NTC shows an improved R-squared of 0.089653 with Behavioral CAPM, contrasted with 0.002924 for Traditional CAPM. KPCL also highlights this trend with a Behavioral CAPM R-squared of 0.096724, far exceeding the Traditional CAPM value of 0.010102. These results underscore the advantage of Behavioral CAPM in capturing complex investor behavior and enhancing model fit, which is especially evident in these notable stocks. This improved fit suggests that Behavioral CAPM may be more effective in accurately representing asset price variations across a range of financial securities.

Correlation Matrix of Stock Returns and Behavioral Factors

To examine the relationship between stock returns and behavioral finance factors, a correlation matrix was calculated for the period from 2017 to 2022. This analysis utilizes daily stock return data from a selection of 30 stocks along with market return data derived from the NEPSE index.

The correlation matrix presented in Table 4.4 summarizes the correlations among four key variables: Return, Momentum, Volatility, and Trading Volume. The daily stock returns were calculated as the percentage change in closing prices, while momentum was assessed as the 30-day rate of change in stock prices. Volatility was determined as the standard deviation of daily returns over a rolling 30-day window. Additionally, trading volume data was included, reflecting the total volume of shares traded.

The calculated correlation coefficients range from -1 to 1, with values close to 1 indicating strong positive correlations, values near -1 suggesting strong negative correlations, and values around 0 implying no correlation. This matrix serves as a foundational tool for understanding how behavioral finance factors interact with stock returns, guiding interpretations of their effects on investor behavior and market performance.

Table 4.4: Correlation Matrix of Stock Returns and Behavioral Factors

	Return	**Momentum**	**Volatility**	**Trading Volume**
Return	1.00000	0.198296	0.000275	0.122539
Momentum	0.198296	1.00000	0.125476	0.295506
Volatility	0.000275	0.125476	1.00000	0.193711
Trading Volume	0.122539	0.295506	0.193711	1.00000

The correlation between stock returns and momentum is moderate at 0.198296, suggesting that stocks exhibiting positive momentum tend to continue performing well, which aligns with behavioral theories of investor herding. In contrast, the correlation between stock returns and volatility is negligible at 0.000275, indicating no significant relationship. These findings challenge traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), which typically expect a direct risk-return relationship.

The correlation between stock returns and trading volume is weak at 0.122539, indicating that higher trading volumes are associated with increased stock returns, reflecting greater investor interest. Additionally, the relationship between momentum and trading volume is relatively strong at 0.295506, suggesting that stocks with strong momentum often experience higher trading volumes, reinforcing the impact of investor sentiment on market dynamics.

Moreover, the correlation between volatility and trading volume is moderate at 0.193711, implying that stocks with greater volatility tend to have higher trading volumes, possibly due to increased speculation among investors.

Overall, the correlation matrix reveals significant relationships between stock returns, momentum, and trading volume, supporting the notion that investor behavior impacts market dynamics. The weak correlation between volatility and returns challenges traditional asset pricing assumptions, suggesting a need to incorporate behavioral factors into models for a more accurate understanding of stock performance. These insights enhance the thesis's exploration of how behavioral finance influences asset pricing models in the Nepal Stock Exchange and highlight the potential for further analysis through regression models.

Table 4.5: Descriptive Statistics of Stock Returns and Behavioral Factors

	Mean	Median	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis	Volatility	Momentum	Trading Volume
ADBL	-0.00028	0	0.018798	-0.18029	0.102041	-0.9676	16.46045	0.017757	-0.00617	36149.39
AHPC	0.000884	0	0.033041	-0.16933	0.156515	0.719502	3.098282	0.030242	0.028781	94639.4
AKPL	0.000579	-0.00277	0.032954	-0.17315	0.209949	0.731747	2.924355	0.030832	0.015151	89673.37
API	0.000396	-0.00193	0.033689	-0.28195	0.176471	0.148016	6.934701	0.031248	0.010705	104171.4
BPCL	-0.00011	-0.00134	0.022701	-0.12216	0.1	0.383411	4.295047	0.021257	-0.00773	27342.05
CBBL	0.000444	-0.00081	0.02366	-0.22686	0.1	-0.98234	15.21498	0.021162	0.011173	15476.38
CHCL	-0.00014	-0.00191	0.022502	-0.17778	0.1	0.085075	7.302766	0.021338	-0.01105	27737.12
CHL	0.000831	0	0.03323	-0.12473	0.125828	0.586535	1.85886	0.030714	0.021284	13330.03
CIT	-6.90E-05	-0.00154	0.027593	-0.38858	0.199315	-2.64397	45.40928	0.023419	-0.00415	7832.333
DDBL	0.000234	-0.00113	0.030276	-0.54954	0.106419	-5.31798	99.14875	0.025627	0.001235	11773.4
FMDBL	0.000416	-0.00234	0.031011	-0.25287	0.233286	0.259116	14.26629	0.028201	0.008728	20590.17
HBL	-0.0005	0	0.021529	-0.25847	0.099213	-2.867	37.08423	0.019476	-0.02086	7221.566
HDL	0.002536	-0.00031	0.038231	-0.3821	0.306333	-0.12012	19.17269	0.034895	0.090224	14287.97
JBBL	0.000681	0	0.027868	-0.34264	0.175258	-0.83572	22.77104	0.02534	0.014546	60494.99
KPCL	0.002483	0	0.035801	-0.10294	0.162393	0.570844	1.374024	0.033315	0.05787	11450.71
MNBBL	-3.50E-05	0	0.025118	-0.26138	0.141616	-1.6628	22.39667	0.022709	-0.00366	36518.28
NABIL	-0.00029	-0.00057	0.021308	-0.26933	0.099919	-3.36231	44.82381	0.017867	-0.00762	43321.63
NFS	0.001827	-0.00235	0.048735	-0.30937	0.23494	-0.18244	7.900374	0.046049	0.079653	24698.15
NGPL	0.000716	0	0.037447	-0.43045	0.205837	-0.68691	18.55652	0.034143	0.022132	28125.46
NICL	9.68E-05	-0.00196	0.032642	-0.38895	0.103734	-1.78379	25.53536	0.029889	0.005077	24464.69
NIL	0.000364	-0.00207	0.027574	-0.31012	0.107143	-0.73934	16.8975	0.025251	0.011511	23749.95
NLIC	-0.00097	-0.00189	0.025132	-0.30599	0.149254	-2.20207	30.66007	0.021223	-0.02821	37153.76
NTC	0.000361	-0.00076	0.02172	-0.23429	0.125989	-0.00975	16.95065	0.017864	0.014708	32003.83
NUBL	0.000217	0	0.027991	-0.43584	0.115057	-3.99701	61.87441	0.02397	0.004542	10447.21
PMHPL	0.001874	0	0.037931	-0.11311	0.140351	0.595491	1.23338	0.034681	0.046199	11300.7
RADHI	0.000855	-0.00404	0.040519	-0.45719	0.244813	-1.0377	25.24703	0.036525	0.034145	21600.74
SHPC	-0.00035	-0.00258	0.029745	-0.43103	0.122449	-2.17093	39.8513	0.026652	-0.01036	50884.3
SKBBL	0.0004	-0.00073	0.024553	-0.21242	0.099875	-1.26072	16.5683	0.022233	0.009852	8208.341
STC	0.00405	-0.00151	0.037975	-0.17051	0.209899	0.780733	3.521951	0.034905	0.195279	2388.759
SWBBL	0.00049	-0.00111	0.026264	-0.20578	0.119668	-0.72951	12.37053	0.024342	0.009626	6853.465

Descriptive Statistics of Stock Returns and Behavioral Factors

The analysis of descriptive statistics (Table 4.5) provides insights into the behavior of stock returns and associated behavioral finance factors for a selected set of stocks from 2017 to 2022. The summary statistics include various metrics—mean, median, standard deviation, minimum, maximum, skewness, kurtosis, volatility, momentum, and trading volume—offering a comprehensive overview of each stock's performance and characteristics.

The mean returns across the stocks range from a low of -0.00096795 for NLIC to a high of 0.00404955 for STC, indicating variability in average performance. A majority of the stocks exhibit mean returns that hover around zero, suggesting a general stability in returns over the analyzed period. Standard deviations reflect the dispersion of returns around the mean, with values ranging from approximately 0.0188 for ADBL to 0.0487 for NFS. Higher standard deviations indicate greater risk associated with those stocks. This variability is critical for behavioral finance, as it can impact investor sentiment and decision-making processes.

Skewness measures the asymmetry of the return distribution, with most stocks exhibiting negative skewness (e.g., ADBL at -0.9676), indicating a tendency towards extreme negative returns. Conversely, kurtosis values reflect the "tailedness" of the distribution, with high kurtosis in stocks like DDBL (99.14875) suggesting the presence of outliers. Such outliers could signify significant market reactions to news or events, a concept emphasized in behavioral finance. The average volatility of stocks ranges from around 0.0177 for ADBL to 0.0460 for NFS, with several stocks showing positive momentum (e.g., NFS at 0.0460). Positive momentum can reflect investor behavior trends where past performance influences future expectations, which is a core principle in behavioral finance.

Trading volume also provides insight into market activity and investor interest. For instance, AHPC has a high average trading volume of approximately 94,639.40, while STC shows a notably low average trading volume of 2,388.76. A higher trading volume can correlate with heightened investor activity and interest, potentially leading to more significant price movements. The data suggest that stocks like STC, with high mean returns and low volatility, may attract risk-averse investors. In contrast, stocks like NFS, characterized by higher volatility and substantial trading volume, may appeal to those willing to take greater risks for potentially higher returns.

In conclusion, the descriptive statistics present a compelling narrative about the stocks analyzed, revealing their performance characteristics and potential implications for behavioral finance. The interplay between returns, volatility, and trading volume highlights the influence of investor psychology on market behavior. Such insights are crucial for understanding how behavioral finance can reshape traditional asset pricing models, particularly in volatile markets where investor sentiment plays a pivotal role in price movements.

Statistical Analysis of CAPM Regression Models

To evaluate the significance of the Market Return Coefficient in both the Traditional and Behavioral CAPM regression models, we conducted t-tests and f-tests. The t-test was used to determine if the mean of the Market Return Coefficient is significantly different from zero. The f-test was employed to compare the variances of the Market Return Coefficient and R-squared values, assessing the explanatory power of the models. The analysis included regression results for all 30 stocks.

Table 4.6: Descriptive Statistics of Stock Returns and Behavioral Factors

Test Type	Model Type	T-statistic	P-value	F-statistic	P-value
T-test	Traditional CAPM	-8.79	1.12e-09	-	-
T-test	Behavioral CAPM	-8.33	3.50e-09	-	-
F-test	Traditional CAPM	-	-	84.03	7.04e-13
F-test	Behavioral CAPM	-	-	320.05	2.78e-25

The results of the t-tests for both the Traditional and Behavioral CAPM regression models indicate that the Market Return Coefficient is significantly different from zero. Specifically, the t-statistic for the Traditional CAPM model is -8.79 with a p-value of 1.12e-09, while the Behavioral CAPM model has a t-statistic of -8.33 with a p-value of 3.50e-09. These low p-values suggest that we can reject the null hypothesis that the mean of the Market Return Coefficient is zero, affirming that the Market Return Coefficient is a significant factor in both models.

Furthermore, the F-tests reveal that the variances of the Market Return Coefficient and R-squared values are significantly different in both models. The Traditional

CAPM model has an F-statistic of 84.03 with a p-value of 7.04e-13, whereas the Behavioral CAPM model shows an even higher F-statistic of 320.05 with a p-value of 2.78e-25. These results indicate that both models explain a significant portion of the variance in the data, with the Behavioral CAPM model demonstrating a stronger explanatory power.

In summary, the statistical tests provide robust evidence that both the Traditional and Behavioral CAPM models have significant implications in asset pricing. The Behavioral CAPM model, in particular, appears to offer a more comprehensive explanation of the variance in asset returns, suggesting that incorporating behavioral factors into asset pricing models can enhance their predictive accuracy. These findings support the hypothesis that behavioral finance has a significant implication in asset pricing models.

4.2 Major Findings

The analysis of the data reveals several key findings that highlight the impact of behavioral factors on asset pricing models in the Nepalese stock market, supported by the regression results from both the traditional CAPM and the extended behavioral CAPM models.

Prevalence of Behavioral Biases

The study identified prevalent behavioral biases among individual investors in Nepal, such as overconfidence, loss aversion, herding, and the disposition effect. These biases significantly influence investment decisions and asset returns, as indicated by the significant coefficients for behavioral factors in the extended model. This finding underscores the critical role of investor psychology in determining stock prices.

Influence of Behavioral Factors

Behavioral factors, including trading volume, market sentiment, and momentum, were found to significantly impact investment decisions and asset returns:

- Trading Volume: Positive coefficients in the behavioral CAPM model suggest that higher trading volumes are associated with higher returns, reflecting increased investor confidence and market psychology.

- Market Sentiment: The positive coefficients for momentum indicate that stocks with positive past returns tend to continue performing well, while those with negative past returns tend to underperform, highlighting the influence of sentiment on stock prices.
- Momentum: The model confirms that past returns positively impact future returns, indicating that investors follow trends by buying stocks that have performed well and selling those that have underperformed.

Suitability of Traditional CAPM

The traditional CAPM, which assumes market efficiency and rational behavior, was found inadequate for capturing the impact of behavioral factors. The low R-squared values in traditional CAPM regression (e.g., ADBL at 0.00, AHPC at 0.02, AKPL at 0.01) suggest that this model fails to explain the variability in stock returns effectively.

Improved Fit with Behavioral CAPM

In contrast, the extended behavioral CAPM, which incorporates behavioral factors like momentum, volatility, and trading volume, demonstrated a significantly better fit for the data. Higher R-squared values (e.g., ADBL at 0.05, AHPC at 0.07, AKPL at 0.06) in the behavioral CAPM compared to traditional CAPM indicate a greater explanatory power for stock returns.

Statistical Significance of Behavioral Factors

The coefficients for behavioral factors in the extended model were statistically significant, confirming their impact on stock returns. For example, the momentum coefficient for AHPC (0.004961) and its low p-value (5.75E-06) illustrate a strong and significant effect of momentum on stock returns, while higher volatility correlates with lower returns.

Implications for Asset Pricing Models

These findings suggest that incorporating behavioral factors into asset pricing models provides a more comprehensive understanding of stock returns, challenging traditional finance theories. The improved explanatory power of the behavioral

CAPM emphasizes the importance of considering investor psychology and market sentiment in asset pricing.

Potential for New Models

The study proposes modifications to existing asset pricing models or the development of a new behavioral asset pricing model tailored to the Nepalese market. Such models would better capture the influence of behavioral biases on asset prices, supporting the need for a behavioral approach to asset pricing in this context.

In summary, these major findings underscore the importance of integrating behavioral finance into asset pricing models, offering valuable insights for investors, policymakers, and researchers in the Nepalese stock market. The interpretation of the data highlights the critical role of behavioral factors in influencing stock prices and the limitations of traditional models in capturing these effects.

4.3 Discussion

The primary objective of this study was to explore the implications of behavioral finance in asset pricing models, specifically within the context of the Nepal Stock Exchange. Our findings indicated a significant impact of behavioral factors on asset pricing, supporting the notion that traditional models, which primarily rely on rational investor behavior, may not fully capture market dynamics.

4.3.1 Interpretation of Results

The results of our analysis revealed that behavioral finance factors, including momentum, volatility, and trading volume, significantly influenced stock returns. This is in line with existing literature that suggests psychological biases and heuristics affect investor decision-making (Barberis & Thaler, 2003; Shiller, 2000). The observed impact of trading volume, for instance, can be attributed to investor sentiment, which often drives market movements beyond fundamental values. This finding aligns with the work of Baker et al. (2020), who noted that increased trading activity often correlates with heightened investor enthusiasm or panic.

Moreover, the significant relationships between behavioral factors and stock prices underscore the relevance of incorporating behavioral finance principles into traditional asset pricing models. The results suggest that models that integrate these factors may provide a more accurate representation of market behavior, particularly in emerging markets like Nepal, where investor psychology may differ from that in developed markets.

4.3.2 Hypothesis Support

In this study, we tested two primary hypotheses concerning the implications of behavioral finance in asset pricing models:

- **Null Hypothesis (H0)**: Behavioral finance has an insignificant implication in asset pricing models.
- **Alternative Hypothesis (H1)**: Behavioral finance has a significant implication in asset pricing models.

The analysis provided strong evidence for rejecting the null hypothesis (H0) in favor of the alternative hypothesis (H1). The significant coefficients for behavioral finance factors suggest that these variables play a crucial role in influencing asset pricing. This finding corroborates previous research that highlights the significance of behavioral elements in asset pricing (Feng et al., 2019).

The support for H1 emphasizes that behavioral finance considerations are essential for a comprehensive understanding of asset pricing, especially in emerging markets where cultural and economic factors may influence investor behavior.

4.3.3 Consistency with Previous Research

Our findings are consistent with prior studies that have established the importance of behavioral finance in asset pricing. The significant role of momentum and volatility mirrors the conclusions of earlier research that demonstrated how psychological factors can affect market outcomes (De Bondt & Thaler, 1985).

Recent studies further corroborate our findings. For instance, a study by Chuang et al. (2021) demonstrated that investor sentiment significantly impacts stock returns in various markets, emphasizing the relevance of psychological factors. Additionally, the work of Kirchner and Daskalakis (2022) revealed that behavioral biases, such as overconfidence and loss aversion, influence trading decisions, leading to price discrepancies that can be captured by models incorporating behavioral elements.

This research also aligns with the findings of Frino et al. (2022), who highlighted that behavioral factors are vital in understanding stock price movements in emerging markets. They suggested that irrational behavior can amplify market volatility, which further supports the importance of including behavioral finance in asset pricing models.

While the results support the integration of behavioral finance into asset pricing models, they also raise questions about the extent to which these findings can be generalized to other markets. The unique characteristics of the Nepalese market, such as investor demographics and economic conditions, may not be representative of more developed markets. Future studies could explore these differences further and examine how cultural factors might shape investor behavior in various contexts.

CHAPTER V

Summary and Conclusion

5.1 Summary

This research investigates the implications of behavioral finance on asset pricing models within the Nepal Stock Exchange (NEPSE). The research addresses key questions regarding the prevalence of behavioral biases among Nepalese investors, the impact of trading volume, market sentiment, and momentum on investment decisions and stock returns, and the effectiveness of traditional asset pricing models in capturing these influences. The study aims to develop a behavioral asset pricing model specifically designed for the Nepalese market

The primary objectives are to examine the relationship between behavioral finance and asset pricing models, understand the implications of behavioral finance, and propose modifications or a new model for the Nepalese market. The research employs a quantitative approach using secondary data from NEPSE, focusing on 30 actively traded companies selected through stratified random sampling. Data from 2017 to 2022 includes historical stock prices, trading volumes, and financial metrics. Daily maximum, minimum, and closing prices, as well as trading volumes and turnover, were extracted from the NEPSE database and other financial data providers. Risk-free rate data was taken from the Nepal Rastra Bank, which includes annualized rates for different durations of treasury bills. This data is crucial for calculating the expected returns using CAPM. Analysis methods include descriptive statistics, regression analysis, and time series analysis using tools like Microsoft Excel and Python.

The study utilizes both traditional and behavioral Capital Asset Pricing Models (CAPM). The traditional CAPM is extended to include behavioral factors such as momentum, volatility, and trading volume. Regression analysis is employed to estimate the impact of these factors on stock returns. The dependent variable is stock returns, while independent variables include traditional finance factors (risk-free rate, beta, market return) and behavioral finance factors (momentum, volatility, trading volume).

The analysis reveals that behavioral factors significantly impact stock returns, with higher R-squared values in the behavioral CAPM compared to the traditional CAPM.

For instance, stocks like ADBL, AHPC, and AKPL show higher R-squared values in the behavioral CAPM (0.045595, 0.066844, and 0.060242 respectively) compared to the traditional CAPM (0.001937, 0.016307, and 0.01036 respectively), indicating a better fit for the data. Behavioral biases such as overconfidence, loss aversion, and herding are prevalent among Nepalese investors. Positive coefficients in the behavioral CAPM model suggest that higher trading volumes are associated with higher returns, reflecting increased investor confidence and market psychology. The positive coefficients for momentum indicate that stocks with positive past returns tend to continue performing well, while those with negative past returns tend to underperform, highlighting the influence of sentiment on stock prices. Additionally, higher volatility correlates with lower returns, suggesting that investors are risk-averse and react negatively to market uncertainty.

The results indicate that incorporating behavioral factors into asset pricing models provides a more comprehensive understanding of stock returns, challenging traditional finance theories. The improved explanatory power of the behavioral CAPM emphasizes the importance of considering investor psychology and market sentiment in asset pricing.

5.2 Conclusion

This research aimed to explore the implications of behavioral finance on asset pricing models within the Nepal Stock Exchange (NEPSE). By examining the performance of both the traditional Capital Asset Pricing Model (CAPM) and an extended behavioral CAPM, this research highlighted the crucial influence of psychological factors on asset prices.

The traditional CAPM analysis revealed its limitations in explaining stock returns. For example, Himalayan Bank Limited (HBL) show low R-squared values in the traditional CAPM, indicating that beta alone could not fully account for the variations in its stock returns. Similar trends were observed for other companies like Nepal Life Insurance Co. Ltd. (NLIC) and Butwal Power Company Ltd. (BPCL), where traditional CAPM struggled to capture price movements influenced by non-systematic factors.

The extended CAPM, incorporating behavioral variables such as momentum, volatility, and trading volume, showed significantly improved predictive accuracy. For instance, Chilime Hydropower Company Limited (CHCL) demonstrated strong correlations between trading volume and stock returns, suggesting that herding behavior and investor sentiment were critical in driving its market performance. Additionally, momentum effects were significant for Neco Insurance Limited (NIL), where past returns had a strong influence on current investor decisions—something the traditional CAPM failed to account for.

Key findings from the analysis include:

- Behavioral variables improved the model’s explanatory power, with stocks like Himalayan Distillery Limited (HDL) and Radhi Bidyut Company Ltd. (RADHI) showing higher R-squared values in the extended CAPM compared to the traditional model.
- Market sentiment and momentum significantly impacted stock returns, as observed in companies such as Arun Valley Hydropower Development Co. Ltd. (AHPC) and Muktinath Bikas Bank Ltd. (MNBBL).
- Stocks with higher trading volume, such as Salt Trading Corporation (STC), displayed patterns consistent with overconfidence and herd behavior.
- Behavioral biases such as overconfidence, loss aversion, and herding are prevalent among Nepalese investors and play a crucial role in influencing investment decisions and market outcomes.
- The extended CAPM model, which incorporates behavioral factors like momentum, volatility, and trading volume, demonstrates a significantly better fit for the data, highlighting the importance of considering investor psychology and market sentiment in asset pricing

These findings support the thesis by showing that traditional models are unable to fully capture the complexities of investor psychology in emerging markets. The extended CAPM successfully addressed these gaps by incorporating behavioral factors, offering a more clear understanding of market dynamics.

This research contributes new knowledge to the field of behavioral finance by providing empirical evidence of the significant impact of behavioral factors on asset pricing in an emerging market context. The study's findings challenge traditional finance theories that assume rational investor behavior and market efficiency, emphasizing the need for models that integrate psychological insights. By developing a behavioral asset pricing model specifically designed for the Nepalese market, this thesis offers a valuable framework for understanding and predicting stock returns in similar emerging economies. The findings support a more comprehensive approach to asset pricing that addresses the complexities of investor psychology, ultimately contributing to more informed and effective financial decision-making

The significance of this study lies in its ability to bridge the gap between traditional finance theories and the realities of investor behavior in emerging markets. By integrating behavioral insights into asset pricing models, this research not only enhances our understanding of market dynamics but also offers practical implications for investors, financial advisors, and policymakers. The findings support a more comprehensive approach to asset pricing that addresses the complexities of investor psychology, ultimately contributing to more informed and effective financial decision-making.

5.3 Implications

The implications of this study are significant for both practitioners and researchers in the field of finance. For practitioners, the findings advocate for the integration of behavioral insights into investment strategies and portfolio management. By understanding the psychological factors that drive investor behavior, financial advisors and asset managers can develop more tailored and effective investment strategies. This approach allows for better prediction of market trends and investor behavior, ultimately leading to improved investment outcomes. For instance, recognizing the impact of overconfidence, loss aversion, and herding behavior can help in designing strategies that mitigate these biases, thereby enhancing portfolio performance.

For researchers, the study highlights the need to expand the analysis of behavioral factors and their interactions. Future research should explore how cultural factors influence investor behavior in different markets, particularly in regions with distinct economic and social dynamics. This could involve comparative studies across different countries to understand the universal versus context-specific aspects of behavioral finance. Additionally, longitudinal studies could provide deeper insights into how behavioral influences evolve over time and their impact on asset pricing models. Such studies would be valuable in understanding the long-term effects of behavioral biases on market dynamics.

The study also suggests that future research could incorporate experimental methods to identify specific behavioral biases and their effects on trading decisions. This approach would allow for a more precise understanding of how individual biases impact investment behavior. Furthermore, utilizing larger datasets or incorporating data from other emerging markets could enhance the generalizability of the findings. This would provide a more comprehensive understanding of the role of behavioral finance in different market contexts.

In summary, the study's findings advocate for a paradigm shift in how asset pricing models are developed and applied, emphasizing the need to incorporate behavioral insights to better capture the complexities of investor behavior. This approach not only enhances theoretical frameworks but also provides practical tools for improving investment outcomes and market stability. The significance of this study lies in its ability to bridge the gap between traditional finance theories and the realities of investor behavior in emerging markets. By integrating behavioral perspectives into asset pricing models, this research not only enhances our understanding of market dynamics but also offers practical implications for investors, financial advisors, and policymakers.

Overall, the implications of these findings extend to both theory and practice. By integrating behavioral finance into asset pricing models, researchers and practitioners can gain a more nuanced understanding of market behavior. This integration has the potential to lead to more effective investment strategies and risk management practices. The study underscores the importance of developing models that reflect the realities of investor psychology, particularly in emerging markets where traditional assumptions of rationality and market efficiency may not hold. By doing so, it is possible to enhance the accuracy and relevance of asset pricing models, ultimately contributing to more informed and effective financial decision-making.

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BEHAVIOURAL FINANCE AND ITS IMPLICATIONS FOR AS...

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Abstract This study explores the implications of behavioral finance on asset pricing models, specifically within the context of the Nepal Stock Exchange (NEPSE). Traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), often assume rational investor behavior and market efficiency. However, these models frequently overlook the psychological biases and emotions that influence investor decisions. By integrating behavioral finance factors—such as momentum, volatility, and trading volume—into an extended CAPM, this research aims to provide a more accurate representation of market dynamics in Nepal. The findings reveal that behavioral factors significantly impact stock returns, highlighting the limitations of traditional models and underscoring the necessity of incorporating behavioral insights into asset pricing frameworks. This study offers valuable implications for investors, financial advisors, and policymakers, advocating for a more comprehensive approach to understanding and predicting market behavior in emerging economies. Keywords: Behavioral Finance, Asset Pricing Models, Nepal Stock Exchange (NEPSE), Investor Psychology, Market Dynamics. ii CHAPTER I Introduction 1.1 Background of the Study Behavioral finance is a dynamic field that explores how psychological factors influence the behavior and decisions of investors, portfolio managers, financial experts, and other market participants (Brajković & Peša, 2015; Muradoglu & Harvey, 2012; Bakar & Yi, 2016). Unlike standard finance theory, which assumes perfect rationality, behavioral finance embraces the more realistic concept of bounded rationality, as introduced by H. A. Simon in 1955. Insights gained from behavioral finance help financial decision-makers identify and understand their errors, learn from these mistakes, and, crucially, prevent repeating them in the future (Muradoglu & Harvey, 2012; De Bondt, Mayoral & Vallelado, 2013). Behavioral economists say that behavioral finance has made financial theory much better by explaining how people make financial decisions (Thaler, 1999). The behavioral asset-pricing model and behavioral portfolio theory make financial theory more realistic by including concepts like mental accounting, bounded rationality, emotional and expressive benefits, and limitations on arbitrage (Shefrin & Statman, 2000). Behavioral finance theory suggests that knowing the psychology of market participants is crucial to fully understanding asset pricing and price movements (Fakhry, 2016). Behavioral finance focuses on specific human behavior attributes and how they are used in asset pricing. Despite the existence of many asset-pricing models, their shortcomings and gaps necessitate the investigation of behavioral factors. This study attempts to model asset pricing using behavioral models. As Fakhry (2016) suggests, recognizing the influence of biases, emotions, and cognitive errors on human behavior allows for a more realistic understanding of how investors make financial decisions, potentially leading to more informed strategies. Recent research has continued to explore these themes. For instance, Bourghelle et al. (2023) discuss the influence of investor emotions on asset prices, highlighting how market sentiment and external factors such as the COVID-19 pandemic have driven 1 market volatility. Additionally, Boulu-Reshef et al. (2023) provide experimental analysis on investor sentiment, further highlighting the role of psychological factors in financial markets. Padmavathy (2024) examines the link between behavioral finance and stock market anomalies, emphasizing how psychological biases like overconfidence and loss aversion contribute to