Major Research Project

On

FINANCIAL RISK ANALYTICS OF INDIAN SMALL AND MID-CAP STOCKS: A QUANTITATIVE APPROACH

Submitted By

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CERTIFICATE

This is to certify that the Major Research Project report titled "**Financial Risk Analytics of Indian Small and Mid-Cap Stocks: A Quantitative Approach**" is submitted by **Shruti Goel**, roll no. **23/DMBA/119** to Delhi School of Management, Delhi Technological University, in partial fulfillment of the requirement for the award of the degree of Masters in Business Administration during the academic year 2024–2025.

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DECLARATION

I, **Shruti Goel**, hereby declare that the Major Research Project Report entitled "**Financial Risk Analytics of Indian Small and Mid-Cap Stocks: A Quantitative Approach"** submitted to Delhi Technological University is a record of my original work done submitted to **Dr. Chandan Sharma, Assistant Professor, Delhi School of Management, Delhi Technological University**. This project report is submitted in partial fulfilment of the requirements for the award of the degree of MBA in Finance and Analytics.

I also declare that this project report has not been submitted to any other university or institute for the award of any degree or diploma.

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EXECUTIVE SUMMARY

This research project investigates the **financial risk landscape of Indian small- and mid-cap (SMID) stocks** using a multidimensional and quantitative framework. The study emerges from the increasing vulnerabilities faced by SMID firms due to their limited financial buffers, lower institutional coverage, and greater exposure to macroeconomic shocks compared to large-cap companies. The goal is to develop an integrated, data-driven risk assessment system to identify early signs of financial distress and help stakeholders make informed decisions.

The study evaluates three primary dimensions of financial risk:

1. **Credit Risk**, using:
    - Altman Z-Score
    - Debt-to-Equity Ratio
    - Interest Coverage Ratio
    - Debt-to-Asset Ratio
2. **Liquidity Risk**, assessed through:
    - Current and Quick Ratios
    - Working Capital to Sales Ratio
    - Cash Conversion Cycle
    - Composite score of above 3 factors
3. **Market Risk**, analyzed via:
    - Beta (Systematic Risk)
    - Annualized Return Volatility
    - Sharpe and Treynor Ratios suggesting diversification & efficient & underperforming stocks
    - GARCH models to understand volatility clustering using K-means Clustering

The project employs machine learning techniques, particularly the Random Forest algorithm, to classify companies into Low, Medium, and High-Risk categories. Python and Excel were used for data handling, model development, and analysis. The model achieved 89% accuracy, highlighting strong predictive capability, especially for identifying Low and High-Risk firms.

The dataset includes 140 non-financial companies from the Nifty Midcap 100 and Nifty Smallcap 100 indices, analyzed over a single financial year. Sector-wise breakdowns reveal that telecom, power, and healthcare sectors are disproportionately represented in high-risk zones, while FMCG, IT, and capital goods sectors are financially healthier. Mid-cap firms, in general, showed better financial robustness than small-cap counterparts.

Key findings indicate:

- 88–90% of firms are in the "Safe" zone per Altman Z-score, but a critical minority remains in the "Distress" zone.
- Small-cap firms exhibit higher liquidity and credit risk.
- Risk & Return trade-off has been shown using Sharpe & Treynor ratio analysis
- GARCH models confirm volatility clustering, especially in sectors sensitive to macroeconomic trends.

The study provides actionable insights for:

- Investors: Improved portfolio decisions by flagging risky stocks.
- Lenders and Analysts: Early warning signals for credit assessments.
- Policymakers and Regulators: Sector-specific risk management strategies.

By combining traditional ratio analysis, machine learning classification, and econometric modeling, the research offers a holistic financial risk assessment framework tailored for the Indian SMID segment. It bridges the gap between academic theory and real-world financial risk management, contributing meaningfully to the fields of investment analytics and systemic risk detection.

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Financial risk is the likelihood of financial loss by an investor or a firm due to such uncertainty as bad financial choices, market volatility, economic recession, or business setbacks.

Sources of Financial Risk:

- Decreasing revenues or earnings
- Excessive debt or weak cash position
- Interest rate volatility
- Volatility in currency (in case of firms with foreign exposure)
- Weak internal controls or governance problems
- External shocks (such as pandemics, geo-political tensions)

Significance of Financial Risk:

1. To Avert Capital Loss: Investors use financial risk analysis to steer clear of investing in potentially risky or poorly performing firms. Aids to detect warning signs of distress such as weakening liquidity, eroding margins, or increasing debt.

2. To Facilitate sound decision-making: Assists management in taking prompt action—such as cost cutting, debt restructuring, or governance improvement—to avoid lasting harm.

3. To guide lending and credit decisions: Financial indicators of risk are used by banks and lenders to determine when, if, at what rates, and on what terms to lend. Lowers the risk of defaults and non-performing assets (NPAs).

4. To Increase Market Confidence: Successful financial risk management enhances market investor confidence and augments a firm's market capitalization. Low-risk profile companies receive more stable funding and long-term investors.

5. To Prevent Systemic Disruptions: Big defaults (IL&FS, DHFL, Yes Bank) illustrate how the financial risk of one component propagates to the overall system—felling credit markets, investors' psyche, and even GDP.

1.1.1 Indian Equity Market –Small & Mid-Cap Stocks

1. India's Stock Market – A Key Growth Engine

India possesses one of the world's most vibrant and fast-growing stock markets, regulated mainly by SEBI (Securities and Exchange Board of India).

Two of the major stock exchanges—NSE (National Stock Exchange) and BSE (Bombay Stock Exchange)—provide a platform where companies raise capital and investors earn money.

2. Size-based Classification of Companies

Companies listed on the stock exchange are broadly categorized by market capitalization (market cap = share price × number of shares).

- Large-Cap: Market cap above ₹50,000 crores – established, large players like Reliance, TCS, HDFC Bank.
- Mid-Cap: Market cap between ₹10,000–₹50,000 crores – up-and-coming players with great potential.
- Small-Cap: Market cap below ₹10,000 crores – young firms, often innovative or niche players.

3. Focus on Mid & Small-Cap Firms (SMID Segment)

They are not titans, but they are typically in the growth phase, ready to rise.They are leading companies in emerging industries, risky in their endeavors, and are key contributors to:

- India's GDP growth
- Employment generation
- Industrial and local area development
- Competition and innovation

4. Nifty Midcap 100 & Nifty Smallcap 100 – The Sensitive Indices

These are specifically chosen indices by the NSE for tracking the largest 100 mid-cap and smallest cap companies, respectively. They provide an indication of India's growth companies' health and performance. Industry coverage: IT, pharma, manufacturing, renewals, FMCG, etc.

5. Financial Risks of SMID Companies

Although the growth potential is high, these companies also carry a greater financial risk, including:

- Less analyst/institutional coverage – Fewer publicly available data or expert opinions.
- Lower liquidity – shares not traded as frequently, and this can cause price fluctuations to become unstable.
- Weaker balance sheets – less financial buffer to fall back on during tough times.
- Greater sensitivity to external shocks such as interest rate hikes, inflation, or global downturns.

6. Reasons for Investors to use them

Despite the risks, investors find SMID stocks appealing because: They have high potential returns ("alpha generation"). History shows mid and small-cap indices to have often outperformed large-cap indices in recovery cycles—e.g., post-COVID (2021–2022).

7. Importance of Risk Analysis

The same characteristics that lead to growth—aggression, risk-taking, less regulation—can also lead to:

- Financial distress
- Failure of corporate governance
- Sudden collapses

To separate quality stocks from poor ones, we need a structured and analytical approach to assessing financial risk. Especially in the case of SMID companies, detection of risk early enough can protect investors, improve policy development, and ensure long-term market stability.

1.1.2 The Rise of Financial Risk in Indian Markets

Over the years, India's financial markets have grown impressively—but not without facing major bumps along the way. Several high-profile corporate failures and financial crises have shown us just how important it is to spot financial risks early—

especially when it comes to small- and mid-cap companies, which tend to be more vulnerable.

Real-life incidents that shook the Indian financial system:

IL&FS Crisis (2018)

IL&FS, a major shadow bank, defaulted on its payments.It triggered panic across debt markets, mutual funds, and even impacted companies indirectly linked to IL&FS. One big default can spread risk across the system, especially when many firms are connected through credit chains.

Yes Bank Collapse (2020)

One of India’s top private banks faced a crisis due to lending heavily to high-risk borrowers—including several mid-cap companies. Depositors and investors lost confidence, forcing the RBI to step in and rescue the bank. Weak credit checks and aggressive lending can lead to serious financial instability.

DHFL Default

Dewan Housing Finance Ltd. collapsed after being caught misusing funds and lending carelessly. It exposed serious flaws in due diligence and brought tighter rules for NBFCs (non-banking financial companies). SMID companies often depend on NBFCs for loans, so this had ripple effects across many sectors.

Jet Airways & Zee Entertainment

Jet Airways: The airline ran into deep debt due to poor planning and management, eventually shutting down.

Zee: The media giant struggled with debt and governance issues, leading to a rating downgrade and trust issues in the market. Even well-known brands can fail if financial risks aren’t managed properly.

All these examples show a common pattern of financial risk:

Credit issues often go hand-in-hand with poor governance and lack of transparency. Liquidity problems arise when companies are overleveraged or overly dependent on one source of funding. Many of these risks are hard to detect early, especially in smaller firms where financials may not be scrutinized as closely.

1.1.3 Focus on Small- and Mid-Cap Companies for Financial risk

1. High Growth

Small and mid-sized companies are often fast-growing and filled with potential. They're usually in emerging or niche sectors, like green energy, specialty chemicals, digital services, or mid-tier manufacturing. When economic conditions are right, they have the ability to grow faster than large-cap firms, making them very attractive to investors.

2. More Sensitive to Ups and Downs

These companies often don't have deep financial reserves, so even small shocks—like a hike in interest rates or a slowdown in demand—can hit them hard. They are more exposed to changes in the economy, global markets, and government policy.This makes them a great indicator of how economic shifts affect the real business world, especially on the ground level.

3. Less Scrutiny, More Unknowns

While large-cap companies are followed by dozens of analysts and news outlets, many SMID firms get very little attention. This lack of coverage can create information gaps, where important financial risks go unnoticed until it's too late. As a result, there's a higher chance of surprises—good or bad—in these companies.

4. Heavier Financial Risk Exposure

Smaller firms may not have the same risk management systems or governance strength as large corporations. They often rely heavily on bank loans or personal funding from promoters, which can become problematic in tough times. Issues like weak internal controls, poor transparency, or over-dependence on one market or product are more common in this group. All this means that financial risks—like credit risk, liquidity risk, or even bankruptcy—are more concentrated in these companies.

5. Trouble Beginning Signs

Small and mid-cap companies are often the first to show signs of financial stress when the economy falters. This makes them a great segment to watch for early warnings—much like a canary in a coal mine.Studying them helps in understanding how financial risk spreads through the market, especially in challenging times.

6. Better Decisions for Everyone

Understanding financial risk in this space is not just academic—it helps real people:

In short, small- and mid-cap companies may be smaller in size, but they play a huge role in understanding market dynamics and financial risk. They offer a clear window into how companies behave under pressure and how financial health can be tracked, managed, and improved.

1.1.4 Types of Financial Risks

<u>1.Credit Risk</u>

Credit risk is the chance that a company won't be able to pay back what it owes—whether to banks, bondholders, or other lenders.

We look at how likely they are to default (probability of default), how much is at stake (exposure at default), and how big the losses could be if things go wrong (loss given default).

In India's fast-evolving capital market landscape, credit activity plays a central role. It's how capital moves—whether through banks financing a startup's next growth phase, or NBFCs lending to MSMEs in emerging sectors. For the small- and mid-cap (SMID) firms that form the backbone of India's growth engine, access to credit can mean the difference between rapid expansion and operational stagnation. But with opportunity comes risk.

Credit risk refers to the chance that a borrower—be it a listed company or a privately held firm—might fail to repay debt or meet financial commitments. For India's SMID segment, which often operates on thinner margins and faces volatility from global shocks, this risk is especially pronounced.

Several recent episodes—from IL&FS and DHFL to debt-laden mid-cap firms—have underlined how quickly credit issues can spiral into full-blown financial crises.

These events have made risk detection and predictive modeling a necessity rather than an academic exercise.

In India, corporate defaults often stem from a mix of internal mismanagement and external stress.

Most common contributors: Excessive leverage and poor capital structure, falling revenues or profit margins during economic downturns, Overdependence on promoters or limited access to institutional funding, Unhedged exposure to interest rates or commodity cycles, Inadequate financial controls or governance lapses

When a company defaults, it doesn't just affect shareholders—it impacts banks, bondholders, regulators, and even mutual funds. Hence, early detection matters.

To assess credit risk effectively, analysts continue to rely on time-tested financial ratios. These indicators help flag distress signals early—even before defaults happen.

1. <u>Altman Z-Score</u>

- A statistical model that combines multiple accounting ratios to predict bankruptcy risk.
- Formula with Key components:

  $Z=1.2A+1.4AB+3.3C+0.6D+0.99E$

  - A=Working capital/Total assets
  - B=Retained earnings/Total assets
  - C=EBIT/Total assets
  - D=Market value of equity/Total liabilities
  - E=Sales/Total assets

- If $Z > 2.99 \rightarrow$ "Safe"
- If $1.81 < Z \leq 2.99 \rightarrow$ "Grey Zone"
- If $Z \leq 1.81 \rightarrow$ "Distress Zone"

2. <u>Debt-to-Equity Ratio (D/E)</u>

- Total Debt ÷ Shareholders' Equity: A high D/E ratio suggests the company is heavily reliant on borrowed money, which can be risky if interest rates rise or cash flows decline.

- Many mid-cap companies in sectors like infrastructure, real estate, and telecom have historically shown excessive leverage, making this ratio a key red flag.

3. Interest Coverage Ratio (ICR)

- EBIT ÷ Interest Expense: How easily a company can pay interest on outstanding debt. An ICR below 1.5 is considered dangerous. It means the firm is close to struggling with its interest payments.
- After the COVID-19 shock, many mid-sized firms saw this ratio fall sharply—especially in travel, hospitality, and retail.

4. Debt-to-Asset Ratio

- Total Debt ÷ Total Assets: It measures what portion of a company's assets is funded by debt.
- A high debt-to-asset ratio signals greater financial fragility and less asset protection for creditors in case of liquidation.

2. Market Risk – How Volatile is the Stock?

This refers to losses due to swings in stock prices, interest rates, or even currency values. In SMID stocks, these movements tend to be sharper and more unpredictable.

1. Annual Returns

Annual return is the percentage change in the value of an investment over the course of a year. This includes both capital gains (price appreciation) and dividends (earnings paid out to shareholders).

- These returns fluctuate due to:
    - **Macroeconomic factors**: Changes in interest rates, inflation, and economic cycles.
    - **Company performance**: The health and profitability of the company you're investing in.
    - **Investor sentiment**: The overall mood of the market (optimistic or pessimistic).

- **Market volatility**: Periods of high market movement (like a financial crisis) can drastically impact returns.

2. Systematic Risk and Beta

Systematic risk (also known as market risk) refers to risks that affect the entire market. Examples include economic recessions, interest rate hikes, and geopolitical events (e.g., wars or natural disasters). This type of risk cannot be diversified away because it impacts all stocks.

Beta (β) is a measurement that helps understand how a stock reacts to changes in the overall market.

- **$\beta > 1$**: The stock is more volatile than the market (if the market moves 1%, this stock might move 2%).
- **$\beta < 1$**: The stock is less volatile than the market (if the market moves 1%, this stock might move 0.5%).
- **$\beta = 1$**: The stock moves in line with the market (if the market moves 1%, the stock moves 1%).

Investors use beta to decide how much market risk they want in their portfolio. For example, high-beta stocks can offer higher returns but also come with more risk, while low-beta stocks are more stable but offer potentially lower returns.

3. Volatility: A Historical Perspective

Volatility is typically measured using standard deviation, which quantifies the variation in returns over time. Historically, stock market volatility has averaged around 20% per year, but it can vary greatly based on global and domestic events.

4. Uncertainty and Its Role in Volatility

Uncertainty is a natural part of financial markets and contributes to volatility. When there's uncertainty about future events, stock prices can fluctuate widely, causing larger swings in the market. Upward stock movements usually align with lower volatility, while downward movements tend to cause higher volatility.

Bad news or negative economic shocks (e.g., financial crises) often have a larger impact on the market than good news. Negative shocks tend to create more volatility and greater downward pressure on stock prices.

4. Volatility Across Sectors

Not all sectors of the economy behave the same. For instance, banking stocks may respond differently to interest rate changes compared to technology stocks or consumer goods stocks. Every sector has its own unique fundamentals, such as:

- Regulatory environment (e.g., banking regulations).
- Demand cycles (e.g., tech booms or downturns).
- Global influences (e.g., oil price fluctuations affecting the auto sector).

5. Evaluation of Performance

To make informed decisions, investors rely on performance metrics that measure returns relative to risk:

- **Sharpe Ratio**: Measures the excess return you get for each unit of total risk (standard deviation).
    - Formula: Sharpe Ratio = (Rp – Rf) / SD(,

Rp = Expected portfolio return. Rf = Risk-free rate of return. SD= Standard deviation of portfolio return (or volatility)

- Higher Sharpe ratios indicate that the investment is providing more return for each unit of risk taken.
- It's useful for comparing different portfolios or funds that have varying levels of volatility.

- **Treynor Ratio**: Measures the excess return you earn for each unit of **systematic risk** (beta).
    - Treynor Ratio = (Rp - Rf) ÷ β_p, where Rp is the portfolio return, Rf is the risk-free rate, and β_p is the portfolio beta.

    - Unlike the Sharpe ratio (which considers total risk), the **Treynor ratio** only focuses on **market risk**, which is helpful if your portfolio is well-diversified and not prone to unsystematic risk.

6. Need for Volatility Models (ARCH/GARCH)

- Modeling volatility is a complex task because it involves many phenomena, such as **leverage effects** and the **non-normality of errors** in returns.
- **ARCH** (Autoregressive Conditional Heteroskedasticity) and **GARCH** (Generalized Autoregressive Conditional Heteroskedastic) models are designed to capture volatility and its changing nature over time.
    - These models help explain why stock returns often exhibit **volatility clusters**, where periods of high volatility tend to follow other periods of high volatility, and the same happens with low volatility.
    - Unlike traditional models (like ARMA), which assume a constant **variance over time**, ARCH/GARCH models adapt to time-varying volatility, making them essential tools for managing and forecasting financial risk.

3. Liquidity Risk – Can the Company Stay Afloat When Cash Gets Tight?

Liquidity risk isn't just about stock trading—it's about how well a company manages its cash in real life. It tells us whether the business can meet its short-term needs without scrambling for emergency funds.

How Liquidity Risk Impacts Business

- Creditworthiness: If lenders think your liquidity is weak, they'll either charge higher interest or refuse to lend.
- Operational Stability: Without cash, even daily business gets affected—delayed payments, lost suppliers, missed opportunities.
- Investor Confidence: Markets punish companies with weak liquidity. Share prices drop when investors see funding risks.

Real-World Lessons: Crises Expose Liquidity Weakness: During the **2008 financial crisis**, even good companies collapsed because they ran out of cash.The **COVID-19**

pandemic was another shock—many small and mid-sized firms couldn't survive the revenue drop due to poor liquidity planning.

Mid- & Small-Cap Firms Are More Vulnerable as:

These companies often face **lower trading volumes** and limited investor interest in the stock market. They may not have access to big bank loans or the ability to quickly raise funds like large companies do. A sudden slowdown or **cash crunch** can disrupt their entire operations.

Key Financial Parameters That Help Measure Liquidity Risk:

1. Current Ratio = Current Assets / Current Liabilities

- It shows whether the company has enough short-term assets to pay its short-term debts.
    - **Too low (<1)** → Red flag: company might struggle to pay bills.
    - **Too high (>2)** → May suggest idle assets, not efficiently used.

2. Quick Ratio = (Current Assets – Inventory – Prepaid Expenses) / Current Liabilities

- It's a stricter version of the current ratio—it only considers assets that can quickly be turned into cash.
- Inventory can take time to sell, so this ratio gives a clearer picture of liquidity.
- A small electronics firm with slow-moving stock may look fine on current ratio, but the quick ratio reveals the real liquidity stress.

3. Working Capital to Sales = (Current Assets – Current Liabilities) / Sales

- Tells how much working capital is tied up for every rupee of sales.
    - Very low → Risk of cash crunch if sales suddenly drop.
    - Very high → Funds may be stuck in receivables or inventory.
- A mid-cap FMCG firm with lots of credit sales might have high working capital but cash flow problems.

4. Cash Conversion Cycle (CCC) = DSO + DIO – DPO

- It shows how long it takes to turn inventory and sales into actual cash.

- Longer cycle = higher liquidity risk.
- Breakdown:
    - DSO (Days Sales Outstanding) – How quickly customers pay.
    - DIO (Days Inventory Outstanding) – How long inventory sits.
    - DPO (Days Payables Outstanding) – How long the company takes to pay suppliers.

4. Operational Risk – What Could Go Wrong Internally?

This is about things going wrong inside the company—like fraud, IT system failures, or compliance lapses.

Key factors: Monitoring for fraud, cyber risk, and regulatory adherence is critical here.

- For companies: It can lead to lawsuits, fines, and a tarnished reputation.
- For the market: Events like these reduce investor confidence, especially among retail participants.

5. Business and Industry Risk – What's Happening in the Sector?

These risks are specific to the industry a company operates in—like changing regulations, stiff competition, or disruptive technologies.

Key factors: Earnings trends, industry cycles, and pricing power tell us a lot about how resilient a company is.

- For companies: It could mean inconsistent earnings or the need to change business strategy altogether.
- For the market: Entire sectors may see capital outflows or need government intervention.

reflecting its dominant position in multiple sectors such as financial data and analytics, credit ratings, and market indices.

1.2 PROBLEM STATEMENT

India's small- and mid-cap (SMID) stocks form a fast-evolving yet high-risk segment within the equity market. These firms often struggle with pronounced challenges such as frequent price swings, limited trading liquidity, and strong reactions to macroeconomic changes. Unlike large-cap companies, SMID enterprises usually operate without the safety net of large financial buffers, institutional investment, or mature corporate governance structures—making them more prone to credit risk, liquidity risk, and market shocks. The thin trading volumes and shallow investor participation in these stocks make them even more vulnerable to volatility.

This study aims to analyze these interconnected risk factors and develop an integrated framework to detect financial distress in SMID stocks. By combining descriptive analysis with machine learning-based predictive models, the goal is to generate early warning signals that help investors, financial analysts, and regulators take proactive, well-informed decisions.

1.3 OBJECTIVES OF THE STUDY

<u>1. To Quantify and Evaluate Multi-Dimensional Financial Risk in SMID Stocks</u>
Assess and model the financial risk exposure of small- and mid-cap companies in India over a one-year period by analysing credit risk, liquidity risk, and market risk using both traditional and advanced quantitative techniques. This includes:

A) To assess credit risk:

- Altman Z-Score
- Debt-to-Equity Ratio
- Interest Coverage Ratio
- Debt-to-Asset Ratio
- Zone wise, Sector-wise & Cap-wise stock patterns

B) To evaluate market risk and volatility:

- Beta (systematic risk)
- Annual return volatility

- Sector-wise & Cap-wise stock fluctuations
- Risk/Return performance-Treynor Ratio & Sharpe's Ratio to identify most efficient and most risky stock amongst the most volatile stocks as predicted
- C) To analyze liquidity risk:
- Current Ratio
- Quick Ratio
- Cash Cycle days
- Working Capital/Sales Ratio
- Sector-wise & Cap-wise stock fluctuations

<u>2. To Identify Key Financial and Economic Drivers of Risk</u>

- Financial ratios (e.g., ROE, D/E, ROA etc.)
- Market-based indicators (e.g., price momentum, historical volatility)

<u>3. To Develop Predictive Models using ML and evaluate by ANOVA</u>

Going beyond traditional ratio analysis, this research leverages machine learning—particularly Random Forest—to classify firms based on their risk levels categories-Low Risk, Medium Risk & High Risk. These models are trained on historical financial data (Different Financial Ratios for credit & liquidity risk). This allows for proactive identification of vulnerable companies rather than reactive evaluation.

<u>4. To Analyze Volatility and Market Risk Through GARCH Models</u>

To capture the time-varying nature of market risk, the study applies GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. These models are especially useful in understanding the volatility patterns of SMID stocks.

<u>5. To Offer Actionable Insights for Stakeholders</u>

The final objective is to deliver insights that can help investors, analysts, and financial institutions make informed decisions. By combining risk scores, predictive classifications, and volatility forecasts, the study aims to build an early-warning system that flags high-risk companies well in advance—enabling better investment, lending, and regulatory responses.

1.4 SCOPE OF THE STUDY

This study is focused on evaluating the financial risk landscape of small- and mid-cap (SMID) companies in India, using data from a single financial year. The analysis is based on a carefully chosen sample drawn from the Nifty Smallcap 100 and Nifty Midcap 100 indices.

Companies in this Segment often face higher levels of volatility, weaker financial fundamentals, and heightened exposure to macroeconomic fluctuations. Traditional models like the Altman Z-score and basic ratio analyses provide useful insights but adding a predictive modelling based on Z-score would be able to provide better insights

The study adopts a multi-dimensional approach that leverages modern statistical and machine learning tools to **credit risk**, **liquidity risk**, and **market risk**.

Credit and Liquidity Risk:

The study assessed this through traditional financial ratio models that reflect a firm's ability to meet long-term obligations and employs the Random Forest algorithm—a powerful and widely-used machine learning method—to identify companies at risk of financial distress. By training the model on a set of relevant financial indicators, including solvency ratios, coverage ratios, and operating cash flows, the research aims to:

Liquidity risk assessed using inputs like the current ratio, quick ratio, cash flow from operations, and working capital changes. These helps identify firms that may struggle to meet short-term obligations, even if they appear financially stable at first glance.

Market Risk:

To complement the credit and liquidity analysis, **market risk** is evaluated using the **GARCH** (Generalized Autoregressive Conditional Heteroskedasticity) model. GARCH is particularly effective for modeling time-varying volatility and the clustering of volatility

By combining machine learning (Random Forest) with time series modeling (GARCH), the study provides a comprehensive risk assessment framework.

To carry out this analysis, the study utilizes tools such as **Excel** and **Python.**

Geographically, the study is limited to companies listed in India.

CHAPTER 2

LITERATURE REVIEW

1. Credit Risk Assessment and Prediction

Credit risk evaluation has traditionally relied on financial ratios and structural models; however, recent studies increasingly leverage machine learning techniques for enhanced predictive power. Jiang and Губин (2022) apply Python-based machine learning methods to credit risk assessment, demonstrating superior performance compared to classical statistical models. Their approach uses classification algorithms capable of capturing complex patterns in borrower data, improving the accuracy of credit risk predictions.

In line with this, Cihó (2024) performs a comparative study on BSE-listed companies using the Merton structural model and Altman Z-score. While Altman Z-score, based on accounting ratios, provides a straightforward bankruptcy risk signal, the Merton model incorporates market data and firm value volatility, offering a more comprehensive risk picture. Cihó finds that the integration of market-based variables enhances predictive accuracy, especially in the Indian emerging market context, where accounting standards may vary.

Li et al. (2023) push this frontier by employing deep learning architectures that combine Convolutional Neural Networks (CNN), LSTM networks, and attention mechanisms. Their model captures spatial and temporal dependencies in credit risk data, improving the ability to identify early warning signs of financial distress. This research reflects a growing trend toward hybrid deep learning models in credit risk prediction.

Machine learning and hybrid deep learning models outperform traditional credit risk models, enabling more accurate and timely identification of financial distress, particularly in emerging markets.

2. Liquidity and impact of Liquidity Ratios

Liquidity management is a crucial aspect of corporate finance, balancing the ability to meet short-term obligations with maintaining profitability. Vintilă and Nenu (2016) analyze Romanian listed companies to explore how liquidity ratios influence firm profitability. Their findings suggest a negative relationship between liquidity and profitability, particularly in volatile economic conditions such as the 2008 financial crisis. Companies with excessively high liquidity ratios tend to underutilize their assets, resulting in lower returns on investment. Conversely, too low liquidity increases solvency risk. This highlights the importance of an optimal liquidity level that sustains operational flexibility without compromising profitability.

Similarly, Kumar and Misra (2015) focus on the liquidity characteristics of Indian mid-cap stocks and find that these stocks generally exhibit lower liquidity compared to large-cap stocks. This lower liquidity translates into higher trading costs and more significant price impact during transactions. The study implies that liquidity constraints in mid-cap stocks should be factored into investment decisions, especially for portfolio managers aiming to optimize returns while managing liquidity risk.

Maintaining balanced liquidity is essential for ensuring profitability without exposing firms to liquidity crises; mid-cap stocks require special consideration due to their lower liquidity.

3. Volatility Clustering and Forecasting in Financial Markets

Volatility clustering is a well-documented phenomenon in financial time series where high-volatility events tend to cluster together, followed by periods of relative calm. Mukherjee (2020) investigates this phenomenon specifically in the Indian financial sectors by applying both traditional econometric models and deep learning techniques. Using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, the study captures time-dependent volatility effectively, confirming the persistence of volatility clusters. However, Mukherjee goes further to apply Long Short-Term Memory (LSTM) networks, a type of recurrent neural network capable of learning long-term dependencies and nonlinear patterns in data. The study finds that LSTM models outperform GARCH in forecasting future volatility, highlighting the importance of incorporating machine learning methods alongside classical models. This suggests that hybrid modeling approaches combining econometric and deep learning techniques could provide more accurate volatility forecasts in emerging markets like India.

Incorporating LSTM with traditional GARCH models can enhance volatility prediction accuracy, which is critical for risk management and derivative pricing in financial sectors.

4. Clustering and Segmentation of Mid-Cap Stocks

Segmenting stocks into meaningful clusters helps investors and portfolio managers tailor strategies based on risk and return profiles. Roy and Bhattacharya (2019) apply multivariate data analysis techniques to cluster Indian mid-cap stocks using financial indicators such as earnings per share (EPS), return on equity (ROE), and price-to-book ratio (P/B). Their results reveal distinct clusters within mid-cap stocks, indicating heterogeneity in performance and risk that is often masked when considering mid-caps as a homogeneous group. This suggests the utility of clustering methods for better portfolio diversification and risk management.

Kumar and Misra's (2015) liquidity-focused study complements this by showing that mid-cap stocks suffer from lower liquidity, which can influence cluster characteristics and investment decisions. Hence, clustering approaches that integrate both financial and liquidity variables can offer more robust segmentation.

Multivariate clustering provides valuable insights into mid-cap stock heterogeneity, supporting tailored investment strategies and improved risk management.

5. Predictive Analytics and Financial Risk Assessment

The integration of predictive analytics into financial risk management is transforming how risks are identified and mitigated. Pala (2023) highlights the role of predictive analytics in assessing market risk, stressing how machine learning models can analyze vast datasets to detect patterns and forecast adverse financial events. The study underscores the increasing reliance on data-driven techniques to enhance traditional risk management frameworks.

Al-Yatamai et al. (2020) examine the combined effects of credit, operational, and liquidity risks on the financial performance of insurance companies on the Kuwait Stock Exchange. Their empirical evidence suggests that managing these risks simultaneously is critical for sustaining financial health, emphasizing an integrated risk management approach.

Kou et al. (2019) provide a comprehensive review of machine learning methods for systemic risk analysis across financial sectors. Their study details how algorithms such as random forests, support vector machines, and neural networks can improve early detection of systemic vulnerabilities, offering policymakers and financial institutions tools to avert crises.

Predictive analytics and machine learning offer powerful capabilities for comprehensive risk assessment and early warning, essential for maintaining financial stability.

6. Industry-Specific Credit Risk Modelling

Sector-specific studies also contribute valuable insights into credit risk evaluation. A 2019 study presented at the ICEMSE conference explores logistic regression models for credit risk analysis of listed real estate companies. The study confirms the effectiveness of logistic regression in classifying companies by default risk based on financial ratios, offering a simple yet reliable tool for industry practitioners.

This is complemented by Li et al. (2023) who incorporate advanced deep learning models to enhance credit risk classification accuracy, focusing on listed companies and leveraging temporal and attention mechanisms.

Logistic regression remains a practical baseline for credit risk analysis in specific industries, but integrating deep learning techniques can substantially improve prediction performance.

The reviewed literature collectively emphasizes the value of combining traditional financial models with advanced machine learning methods to enhance volatility forecasting, liquidity and profitability analysis, credit risk assessment, and stock segmentation. Volatility clustering is better modelled with hybrid GARCH frameworks, liquidity requires balanced management and credit risk predictions benefit significantly from machine learning. Clustering mid-cap stocks reveals critical heterogeneity, aiding tailored investment decisions. Finally, predictive analytics and machine learning provide robust tools for systemic risk monitoring and sector-specific credit evaluation, suggesting a future research direction centered on integrated, data-driven financial risk management systems.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Design

- The study employs an explanatory and predictive research design that is a mixture of:
- Descriptive analysis in the learning of past patterns for risk categories for various sectors in mid & small cap firms
- Predictive modeling to predict financial distress via supervised learning
- Time-series econometrics to evaluate market volatility dynamics.
- Overall methodology brings together both quantitative financial ratios as well as sophisticated analytical tools to provide a multi-dimensioned risk assessment framework.

3.2 Data Gathering and Sources

3.2.1 Sample Selection

- The sample are companies listed in the Nifty Smallcap 100 and Nifty Midcap 100 indices.
- Financial Sector companies are excluded due to certain factors & some with inconsistent data availability are not considered. So, out of 200 companies, 140 are finally taken for research.

3.2.2 Time Horizon

- The study is based on data from one financial year for all types of risk analysis.

3.2.3 Data Sources

- Financial data: Screener.in, Moneycontrol, CMIE Prowess, and company annual reports.
- Market data: NSE website and Yahoo Finance for price data and returns.

3.3 Variables

3.3.1 Credit Risk Indicators

- **Altman Z-Score (Z):**

Used to predict the probability of a firm entering bankruptcy within two years.
Formula:

$Z=1.2A+1.4AB+3.3C+0.6D+0.99E$

  - A=Working capital/Total assets
  - B=Retained earnings/Total assets
  - C=EBIT/Total assets
  - D=Market value of equity/Total liabilities
  - E=Sales/Total assets

Z-Score Classification:

Z-Score	**Risk Zone**
Z > 2.99	Safe
1.81 < Z < 2.99	Grey Zone (moderate risk)
Z < 1.81	Distress Zone (high risk)

Other Credit Risk Indicators:

- Debt-to-Equity Ratio (D/E) = Total Debt / Shareholders' Equity
- Interest Coverage Ratio = EBIT / Interest Expense
- Debt-to-Asset Ratio = Total Debt / Total Assets

3.3.2 Liquidity Risk Indicators

- Current Ratio = Current Assets / Current Liabilities
- Quick Ratio = (Current Assets - Inventories) / Current Liabilities
- Working Capital/Sales Ratio = (Current Assets - Current Liabilities)/Sales

- **Cash Cycle Days =** Days Sales Outstanding + Days Inventory Outstanding – Days Payables Outstanding

A **Liquidity Risk Score** is derived by normalizing the above indicators (using composite score formula assigning weights according to importance), with risk levels classified as:

- Low/Medium/High Risk

3.3.2 Market Risk Indicators

- Beta: Beta coefficient(β)=Variance(Rm)/Covariance(Rs,Rm)

  where:Rs=the return on an individual stock Rm=the return on the market (Nifty Midcap100 Index)
  Covariance=how changes in a stock's returns arerelated to changes in the mar ket's returns, Variance=how far the market's data points deviate from their average value

- Annualized Return & Volatility (Standard Deviation)

- GARCH(1,1)-Predicted Volatility

- Treynor Ratio = (Rp - Rf) ÷ β_p, where Rp is the portfolio return, Rf is the risk-free rate, and β_p is the portfolio beta.

- Sharpe Ratio = (Rp – Rf) / SD (Rp = Expected portfolio return. Rf = Risk-free rate of return. SD= Standard deviation of portfolio return (or volatility)

3.3.4 Market-Based Indicators

- Sectoral indices and Price Momentum

3.4 Tools and Software

- Excel: Financial ratio analysis and data preprocessing

- Python: Machine learning (Scikit-learn, Random Forest), statistical analysis (Pandas, NumPy), and data visualization (Matplotlib, Seaborn)

3.5 Methodological Steps

Step 1: Data Cleaning and Preprocessing

- Handling missing values

- Merged Small & Mid Cap Companies Data (Including calculated factors)
- Classification done in excel for Risk Levels using Scores
- Standardizing/normalizing variables for machine learning models

Step 2: Credit and Liquidity Risk Modeling using Random Forest

- Label target companies as High/Medium/Low Risk based on Altman Z-score and liquidity risk score:
- Overall Distribution of Zscore Zones with % age of companies
- Train a Random Forest Classifier using financial ratios, credit risk labelling and liquidity indicators along with labelling of Risk Levels
- Evaluate model performance using Accuracy, Precision, Recall, F1-Score

Step 3: Market Risk Analysis

- Calculated Beta, Volatility using daily returns from Nifty Data
- Calculated Treynor Ratio with its descriptive analysis
- Apply GARCH(1,1) models on daily stock returns to model conditional volatility
- Calculated Sharpe Ratio with its descriptive analysis
- Compare volatility profiles across industries and risk categories
- Predicted Top 10 Volatile Stocks for future market risk exposure

Step 4: Visualization

- Develop interactive visuals of financial health using different graphs for credit risk, liquidity risk & market risk
- Generated correlation heatmaps as well as volatility graphs

3.6 Model Evaluation Metrics

- Classification Models (Random Forest)
- Confusion Matrix

- Accuracy, Precision, Recall, F1 Score
- Time-Series Models (GARCH)
- Conditional Volatility

3.7 Ethical Considerations

- Use of publicly available and ethically sourced data
- No personal or confidential financial information used
- Transparent disclosure of all assumptions and model limitations

3.8 Limitations of the Methodology

- Timeframe limited to a single financial year may not capture longer-term trends
- Excludes qualitative parameters like ESG scores and management practices
- Market shocks (e.g., COVID-like events) are not explicitly modeled
- 140 companies out of 200 are taken due to Data availability & Financial Sector

CHAPTER 4

DATA ANALYSIS, DISCUSSIONS & RECOMMENDATIONS

4.1. CREDIT RISK

S.No.	Name	Cap	Sector	ZScore	Risk_ Zone	Credit_Risk_ Labelling
1	ACC	Mid	Construction Materials	4.75	Safe	Low
2	Adani Total Gas	Mid	Oil Gas & Consumable Fuels	17.39	Safe	Low
3	Aditya Bir. Fas.	Mid	Consumer Services	3.33	Safe	Low
4	Alkem Lab	Mid	Healthcare	8.38	Safe	Low
5	APL Apollo Tubes	Mid	Capital Goods	14.05	Safe	Low
6	Apollo Tyres	Mid	Automobile and Auto Components	3.83	Safe	Low
7	Ashok Leyland	Mid	Capital Goods	3.02	Safe	Low
8	Astral	Mid	Capital Goods	15.24	Safe	Low
9	Aurobindo Pharma	Mid	Healthcare	4.75	Safe	Low
10	B H E L	Mid	Capital Goods	3.45	Safe	Low
11	Bharat Dynamics	Mid	Capital Goods	9.55	Safe	Low
12	Bharat Forge	Mid	Automobile and Auto Components	6.46	Safe	Low
13	Biocon	Mid	Healthcare	2.05	Grey	Medium
14	Cochin Shipyard	Mid	Capital Goods	6.41	Safe	Low
15	Coforge	Mid	Information Technology	8.7	Safe	Low
16	Colgate-Palmoliv	Mid	Fast Moving Consumer Goods	40.55	Safe	Low
17	Container Corpn.	Mid	Services	7.12	Safe	Low
18	Cummins India	Mid	Capital Goods	17.97	Safe	Low
19	Dixon Technolog.	Mid	Consumer Durables	12.2	Safe	Low
20	Escorts Kubota	Mid	Capital Goods	7.42	Safe	Low
21	Exide Inds.	Mid	Automobile and Auto Components	4.63	Safe	Low
22	FSN E-Commerce	Mid	Consumer Services	26.71	Safe	Low
23	Glenmark Pharma.	Mid	Healthcare	6.62	Safe	Low
24	GMR Airports	Mid	Services	3.32	Safe	Low
25	Godrej Propert.	Mid	Realty	3.54	Safe	Low
26	H P C L	Mid	Oil Gas & Consumable Fuels	3.52	Safe	Low
27	Hindustan Zinc	Mid	Metals & Mining	11.86	Safe	Low
28	I R C T C	Mid	Consumer Services	16.85	Safe	Low
29	Indraprastha Gas	Mid	Oil Gas & Consumable Fuels	5.24	Safe	Low
30	Indus Towers	Mid	Telecommunication	5.06	Safe	Low
31	IRB Infra.Devl.	Mid	Construction	1.91	Grey	Medium

32	Jubilant Food.	Mid	Consumer Services	10.45	Safe	Low
33	Kalyan Jewellers	Mid	Consumer Durables	8.96	Safe	Low
34	KPIT Technologi.	Mid	Information Technology	14.62	Safe	Low
35	Lupin	Mid	Healthcare	8.48	Safe	Low
36	Mankind Pharma	Mid	Healthcare	15.69	Safe	Low
37	Marico	Mid	Fast Moving Consumer Goods	21.49	Safe	Low
38	Max Healthcare	Mid	Healthcare	14.53	Safe	Low
39	Mphasis	Mid	Information Technology	7.88	Safe	Low
40	MRF	Mid	Automobile and Auto Components	5.45	Safe	Low
41	Natl. Aluminium	Mid	Metals & Mining	5.11	Safe	Low
42	NHPC Ltd	Mid	Power	2.34	Grey Zone	Medium
43	NMDC	Mid	Metals & Mining	5.19	Safe	Low
44	Oberoi Realty	Mid	Realty	7.11	Safe	Low
45	Oil India	Mid	Oil Gas & Consumable Fuels	2.53	Grey Zone	Medium
46	Oracle Fin.Serv.	Mid	Information Technology	15.51	Safe	Low
47	P I Industries	Mid	Chemicals	10.14	Safe	Low
48	Page Industries	Mid	Textiles	33.48	Safe	Low
49	Patanjali Foods	Mid	Fast Moving Consumer Goods	12.51	Safe	Low
50	Persistent Sys	Mid	Information Technology	18.55	Safe	Low
51	Petronet LNG	Mid	Oil Gas & Consumable Fuels	7.12	Safe	Low
52	Phoenix Mills	Mid	Realty	5.92	Safe	Low
53	Polycab India	Mid	Capital Goods	13.16	Safe	Low
54	Prestige Estates	Mid	Realty	2.67	Grey Zone	Medium
55	Rail Vikas Nigam	Mid	Construction	8.48	Safe	Low
56	S A I L	Mid	Metals & Mining	2.18	Grey Zone	Medium
57	SJVN	Mid	Power	2.15	Grey Zone	Medium
58	Solar Industries	Mid	Chemicals	30.65	Safe	Low
59	Sona BLW Precis.	Mid	Automobile and Auto Components	9.94	Safe	Low
60	SRF	Mid	Metals & Mining	8.61	Safe	Low
61	Supreme Inds.	Mid	Capital Goods	13.3	Safe	Low
62	Suzlon Energy	Mid	Capital Goods	15.56	Safe	Low
63	Tata Comm	Mid	Telecommunication	3.93	Safe	Low
64	Tata Elxsi	Mid	Information Technology	19.5	Safe	Low
65	Tata Technolog.	Mid	Information Technology	9.11	Safe	Low
66	Torrent Power	Mid	Power	5.35	Safe	Low
67	Tube Investments	Mid	Automobile and Auto Components	7.84	Safe	Low

68	UPL	Mid	Chemicals	2.4	Grey	Medium
69	Vodafone Idea	Mid	Telecommunication	0.15	Distress	High
70	Voltas	Mid	Consumer Durables	8.07	Safe	Low
71	A B Real Estate	Small	Forest Materials	3.71	Safe	Low
72	Aarti Industries	Small	Chemicals	4.16	Safe	Low
73	Action Const.Eq.	Small	Capital Goods	13.1	Safe	Low
74	Affle India	Small	Information Technology	13.61	Safe	Low
75	Amara Raja Ener.	Small	Automobile and Auto Components	5.82	Safe	Low
76	Amber Enterp.	Small	Consumer Durables	7.73	Safe	Low
77	Anant Raj	Small	Realty	7.15	Safe	Low
78	Aster DM Health.	Small	Healthcare	7.88	Safe	Low
79	Atul	Small	Chemicals	6.93	Safe	Low
80	Bata India	Small	Consumer Durables	9.64	Safe	Low
81	BEML Ltd	Small	Capital Goods	5.6	Safe	Low
82	Birlasoft Ltd	Small	Information Technology	7.7	Safe	Low
83	BLS Internat.	Small	Consumer Services	13.18	Safe	Low
84	Brigade Enterpr.	Small	Realty	2.92	Grey	Medium
85	Castrol India	Small	Oil Gas & Consumable Fuels	12.76	Safe	Low
86	CESC	Small	Power	2.12	Grey	Medium
87	Chambal Fert.	Small	Chemicals	6.6	Safe	Low
88	Crompton Gr. Con	Small	Consumer Durables	8.75	Safe	Low
89	Cyient	Small	Information Technology	5.51	Safe	Low
90	Delhivery	Small	Services	5.42	Safe	Low
91	Devyani Intl.	Small	Consumer Services	7.66	Safe	Low
92	Dr Lal Pathlabs	Small	Healthcare	17.59	Safe	Low
93	Firstsour.Solu.	Small	Services	7.62	Safe	Low
94	Garden Reach Sh.	Small	Capital Goods	3.96	Safe	Low
95	GE Shipping Co	Small	Services	3.58	Safe	Low
96	Godfrey Phillips	Small	FMCG	13.12	Safe	Low
97	Guj.St.Petronet	Small	Oil Gas & Consumable Fuels	3.57	Safe	Low
98	HFCL	Small	Telecommunication	4.67	Safe	Low
99	Himadri Special	Small	Chemicals	10.92	Safe	Low
100	Hindustan Copper	Small	Metals & Mining	11.85	Safe	Low
101	Indiamart Inter.	Small	Consumer Services	8.12	Safe	Low
102	Inox Wind	Small	Capital Goods	5.77	Safe	Low
103	International Ge	Small	Services	12.56	Safe	Low
104	Inventurus Knowl	Small	Information Technology	15.91	Safe	Low
105	JBM Auto	Small	Automobile and Auto Components	6.94	Safe	Low
106	Jupiter Wagons	Small	Capital Goods	9.63	Safe	Low

107	K E C Intl.	Small	Construction	3.61	Safe	Low
108	Kalpataru Proj.	Small	Construction	2.84	Grey	Medium
109	Kaynes Tech	Small	Capital Goods	17.71	Safe	Low
110	Laurus Labs	Small	Healthcare	7.66	Safe	Low
111	Mahanagar Gas	Small	Oil Gas & Consumable Fuels	5.08	Safe	Low
112	Narayana Hrudaya	Small	Healthcare	11.69	Safe	Low
113	Natco Pharma	Small	Healthcare	6.35	Safe	Low
114	Navin Fluo.Intl.	Small	Chemicals	9.78	Safe	Low
115	NCC	Small	Construction	3.37	Safe	Low
116	Neuland Labs.	Small	Healthcare	15.72	Safe	Low
117	Newgen Software	Small	Information Technology	18.65	Safe	Low
118	PCBL Chemical	Small	Chemicals	3.58	Safe	Low
119	PG Electroplast	Small	Consumer Durables	18.97	Safe	Low
120	Piramal Enterp.	Small	Healthcare	1.13	Distress Zone	High
121	PVR Inox	Small	Media Entertainment & Publication	1.93	Grey Zone	Medium
122	Radico Khaitan	Small	Fast Moving Consumer Goods	14.67	Safe	Low
123	Railtel Corpn.	Small	Telecommunication	5.78	Safe	Low
124	Ramkrishna Forg.	Small	Automobile and Auto Components	5.21	Safe	Low
125	Redington	Small	Services	5.78	Safe	Low
126	Reliance Power	Small	Power	1.37	Distress	High
127	Rites	Small	Construction	4.63	Safe	Low
128	SignatureGlobal	Small	Realty	3.1	Safe	Low
129	Sonata Software	Small	Information Technology	6.15	Safe	Low
130	Swan Energy	Small	Chemicals	3.35	Safe	Low
131	Tata Chemicals	Small	Chemicals	2.33	Grey	Medium
132	Tata TeleservicesMah.	Small	Telecommunication	-4.98	Distress	High
133	Tejas Networks	Small	Telecommunication	4.6	Safe	Low
134	The Ramco Cement	Small	Construction Materials	3.47	Safe	Low
135	Titagarh Rail	Small	Capital Goods	7.72	Safe	Low
136	Trident	Small	Textiles	5.71	Safe	Low
137	Triveni Turbine	Small	Capital Goods	16.77	Safe	Low
138	Welspun Living	Small	Textiles	4.3	Safe	Low
139	Zen Technologies	Small	Capital Goods	13.93	Safe	Low
140	Zensar Tech.	Small	Information Technology	8.19	Safe	Low

Table 4.1: Credit Risk Zone Classification with labelling based on Z-score

A. Descriptive Analysis:

1. Identifying overall distribution of %age of companies based on Z-score Zones

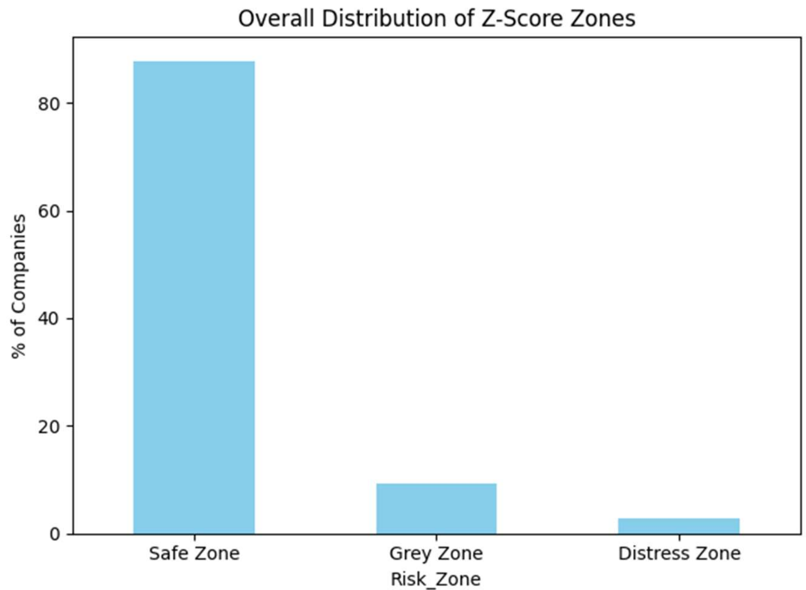

Fig. 4.1 (Source: Own Analysis)

Interpretation:

- This simple bar chart provides a summary of the overall company distribution by Z-score zones in the whole dataset.

Observations:

- Around 88-90% of companies are under Safe, reflecting good financial profiles as a whole.
- A very small percentage (~10%) are under Grey and Distress Zones together.

Insight:

The test population is predominantly healthy firms, but a small minority of the Distress Zone is critical credit risk exposure. Those companies need to be analyzed in more depth within a credit monitoring program.

2. Identifying Cap wise distribution of %age of companies based on Z-score zones

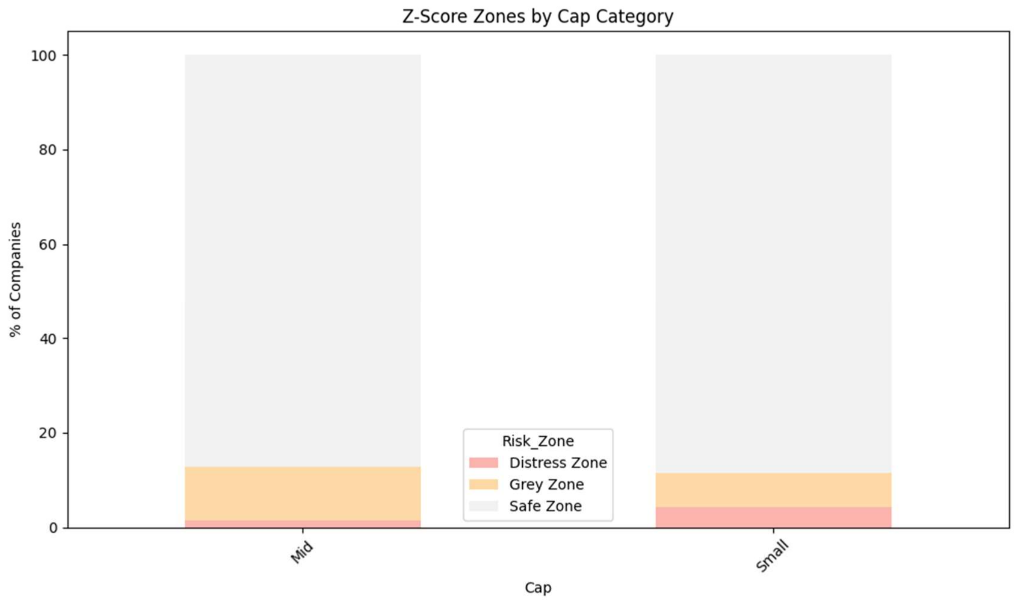

Fig. 4.2 (Source: Own Analysis)

Interpretation:

- This chart shows the proportion of firms in each range of Z-scores (Safe, Grey, Distress), by their Market Cap (Small or Mid).

Observations:

- Both groups contain the majority of firms in the Safe Zone.
- Smallcap companies have a greater proportion in the Distress Zone (~5%) than Midcap (~2%).
- The shape of the Grey Zone is nearly identical for both.

Insight:

Smallcap companies face greater financial distress risk as reflected in their lower mean Z-scores. This is what would be expected under the hypothesis of tighter liquidity and credit access for smaller firms.consumer to another for maximum investment.

3. Identifying Risk Classification Cap Wise (Mid & Small) on companies based on Z-score risk labelling

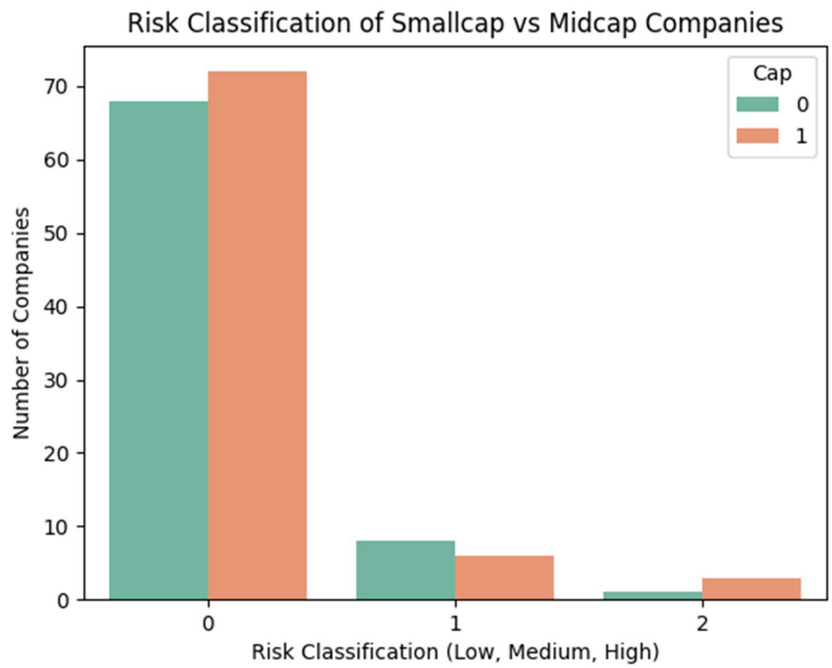

Fig. 4.3 (Source: Own Analysis)

Interpretation:

- This stacked bar chart plots the number of companies in each risk category (0 = Low, 1 = Medium, 2 = High), separated by cap segment (Small = 0, Mid = 1).

Observations:

- Most companies fall under the Low risk category.
- Each cap segment contains a small but evident number of High-risk companies.
- Medium risk portrayal is evened out across both.

Insight:

While the overall base of companies is profitable, there is a tail of High-risk companies in each segment. These would be the ones to follow up with analysis, stress testing, and portfolio trimming if necessary.

4. Identifying Risk Zone Classification-Cap Wise (Both caps) with respect to % of companies based on Z-score

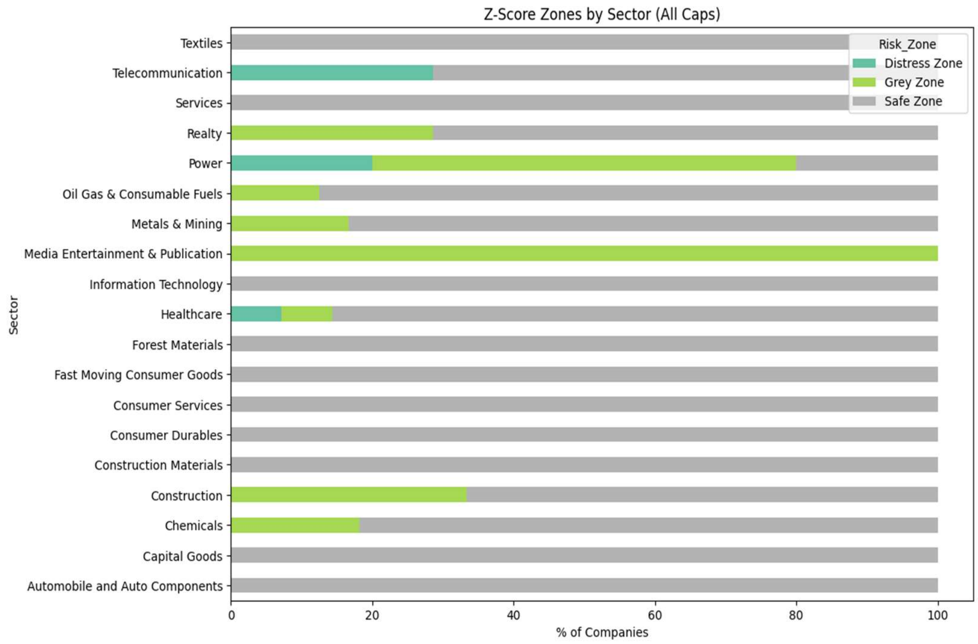

Fig. 4.4 (Source: Own Analysis)

<u>Interpretation:</u>

This is a sector-based holistic perspective which combines both Midcap and Smallcap firms to evaluate sectoral credit risk distribution.

<u>Observations:</u>

Telecom, Power, and Healthcare reveal high proportions in Distress and Grey Zones.

Segments like FMCG, IT, Consumer Services, Capital Goods, and Automobile Components are completely in the Safe Zone.

<u>Insight:</u>

There are evident sectoral patterns in credit risk. Combining sector analysis with cap size gives a multi-dimensional risk view and can guide portfolio construction as well as lending strategy.

5. Identifying Risk Zone Classification-Cap Wise- Mid & Small Cap separately with respect to % of companies based on Z-score

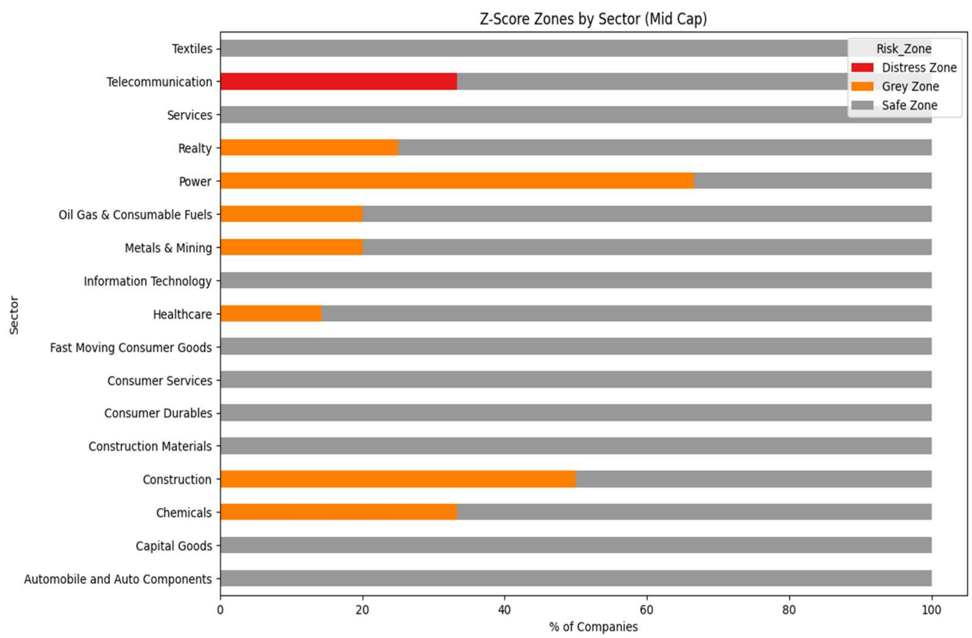

Fig. 4.5 (Source: Own Analysis)

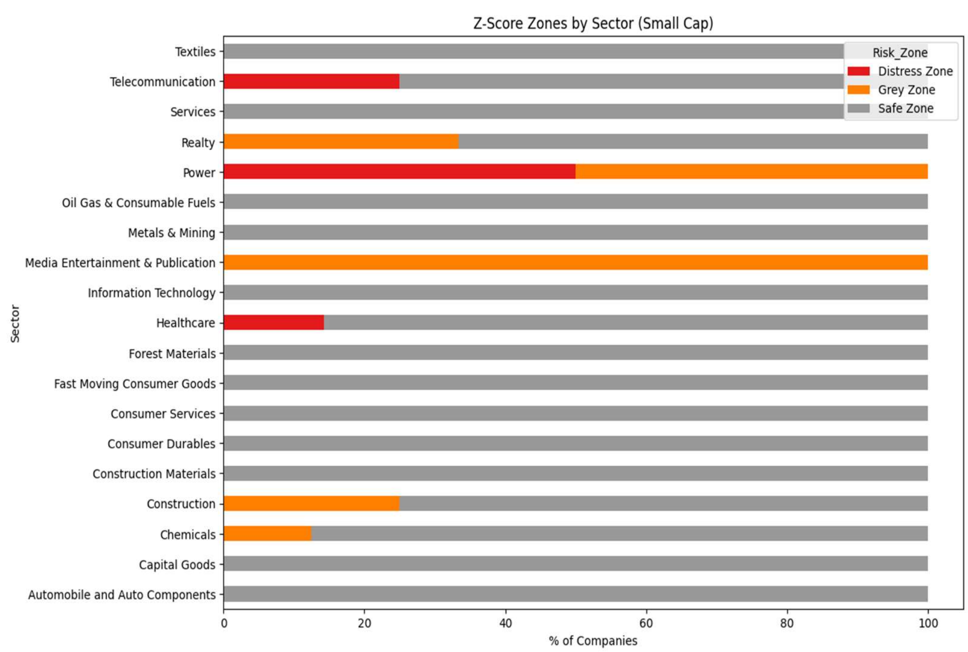

Fig. 4.6 (Source: Own Analysis)

Mid Cap:

Interpretation:

- This is a sector-based holistic perspective with only Midcap firms to evaluate sectoral credit risk distribution.

Observations:

- Telecom reappears strongly in the Distress Zone, indicating chronic financial vulnerability.
- Segments like Power, Construction, and Chemicals are represented highly in the Grey Zone.
- Most Midcap sectors belong to the Safe Zone, consistent with overall better access to capital and healthier balance sheets in mid-sized companies.

Insight:

Midcap players have healthier financial profiles across the sector than Smallcaps. But sector-level weaknesses (particularly in Telecom and Infrastructure) are in line across cap sizes.

Small Cap:

Interpretation:

- This is a sector-based holistic perspective with only Smallcap firms to evaluate sectoral credit risk distribution.

Observations

- Telecom, Power, and Healthcare sectors reflect a relatively higher percentage of companies in the Distress Zone.Media & Entertainment and Realty sectors are largely in the Grey Zone, reflecting financial uncertainty.
- Some sectors like IT, Chemicals, FMCG, and Capital Goods are entirely in the Safe Zone, which reflects good financial robustness of Smallcap firms in these sectors.

Insight

Reflects consolidated risk in a few weak sectors. For credit risk analysts and investors, proportionally high distress sectors need to be identified for in-depth analysis.

6. Identifying Top 10 Mid Cap companies under Credit Risk Categories based on Z-scores

High Risk	Medium Risk	Low Risk	
Vodafone Idea	Biocon	ACC	
	IRB Infra.Devl.	Adani Total Gas	
	NHPC Ltd	Aditya Bir. Fas.	
	Oil India	Alkem Lab	
	Prestige Estates	APL Apollo Tubes	
	S A I L	Apollo Tyres	
	SJVN	Ashok Leyland	
	UPL	Astral	
		Aurobindo Pharma	
		B H E L	

Table 4.2: Top 10 Mid-Cap High Risk, Medium Risk & Low Risk

7. Identifying Top 10 Small Cap companies under Credit Risk Categories based on Z-scores

High Risk	Medium Risk	Low Risk
Piramal Enterp.	Brigade Enterpr.	A B Real Estate
Reliance Power	CESC	Aarti Industries
Tata Teleservices Mah.	Kalpataru Proj.	Action Const.Eq.
	PVR Inox	Affle India
	Tata Chemicals	Amara Raja Ener.
		Amber Enterp.
		Anant Raj
		Aster DM Health.
		Atul
		Bata India

Table 4.3: Top 10 Small-Cap High Risk, Medium Risk & Low Risk

B. Predictive Analysis: Using Python

```
Random Forest Accuracy: 0.8928571428571429
Classification Report:
               precision    recall  f1-score
support

           0       0.96      0.92      0.94        24
           1       0.50      0.67      0.57         3
           2       1.00      1.00      1.00         1

    accuracy                           0.89        28
   macro avg       0.82      0.86      0.84        28
weighted avg       0.91      0.89      0.90        28
```

Fig. 4.7 (Source: Own Analysis)

About Model:

Independent variables: Debt/Equity, Interest-Coverage, Debt/Assets, Sector, Cap for the predictive modelling through Random Forest (supervised algorithm). Encoding & normalization was done. SMOTE was also applied due to imbalanced data set.

Dependent variable: Credit Risk Labelling - Low Risk (0), Medium Risk(1), High Risk(2).

So, the model is trained & tested with data given of 140 companies by splitting the data into 80% train & 20% test data and accordingly results are there.

Model Performance Evaluation

1. Accuracy (89.29%)

- The model is 89.29% accurate overall for financial risk classification (Low/Medium/High). This indicates good general performance; accuracy can be considered based on other class specific measures.

2. Class-Specific Performance

Metric	**Low Risk (0)**	**Medium Risk (1)**	**High Risk (2)**
Precision	0.96	0.50	1.00
Recall	0.92	0.67	1.00
F1-Score	0.94	0.57	1.00

- Low Risk: Excellent performance (96% precision, 92% recall).
- Medium Risk: Good recall but low precision (50%)
- High Risk: Optimal scores (1.00) but on merely 1 sample-so need to be checked with larger data as this is results after applying SMOTE.

Conclusion: The model is extremely good at detecting Low-Risk & High Risk but low in detecting & predict Medium Risk. Overall, the model fits well and can be used for predictions.

4.2. LIQUIDITY RISK

Name	Cap	Column1	Sector	Current_Ratio	Quick_Ratio	WC_Sales	Cash_Cycle_days	CF _Operations	idity_Risk_S	Liquidity_Risk_Label
ACC	Mid	ACC.NS	Construction Mate	1.61	1.27	16.63	32.21	1711.48	2	Low
Adani Tota	Mid	ATGL.NS	Oil Gas & Consum	0.68	0.6	-3.97	2.28	955.13	4	Medium
Aditya Bir.	Mid	ABFRL.NS	Consumer Service	1.01	0.48	17.87	54.88	1341.4	4	Medium
Alkem Lab	Mid	ALKEM.NS	Healthcare	2.66	1.97	63.31	132.41	1948.07	4	Medium
APL Apollo	Mid	APLAPOLL	Capital Goods	1.2	0.55	5.13	-5.23	1111.56	3	Medium
Apollo Tyr	Mid	APOLLOTY	Automobile and A	1.21	0.57	15.01	72.18	3439.52	5	Medium
Ashok Leyl	Mid	ASHOKLEY	Capital Goods	1.15	0.95	33.47	-3.77	-6257.98	4	Medium
Astral	Mid	ASTRAL.NS	Capital Goods	1.8	0.76	16.4	28.84	823.4	4	Medium
Aurobindo	Mid	AUROPHA	Healthcare	1.83	1.1	58.6	215.75	2434.52	6	High
B H E L	Mid	BDL.NS	Capital Goods	1.38	1.08	69.87	51.18	-3712.9	4	Medium
Bharat Dyr	Mid	BHARATFC	Capital Goods	3.05	2.31	257.88	564.46	411.72	4	Medium
Bharat For	Mid	BHEL.NS	Automobile and A	1.04	0.65	38.34	120.9	1664.4	7	High
Biocon	Mid	BIOCON.N	Healthcare	0.96	0.64	24.51	55.15	2953.9	5	Medium
Cochin Shi	Mid	COCHINSH	Capital Goods	1.34	1.08	53.36	154.06	-172.83	6	High
Coforge	Mid	COFORGE.	Information Techr	1.44	1.44	20.64	71.73	903.4	3	Medium
Colgate-Pa	Mid	COLPAL.N	Fast Moving Consu	1.31	1.08	7.91	-113.28	1198.96	2	Low
Container	Mid	CONCOR.I	Services	3.79	3.76	42.45	14.07	1388.5	2	Low

Fig. 4.8 (Source: Own Analysis)

<u>A. Descriptive Analysis:</u>

1. Identifying overall distribution of %age of companies based on Z-score Zones

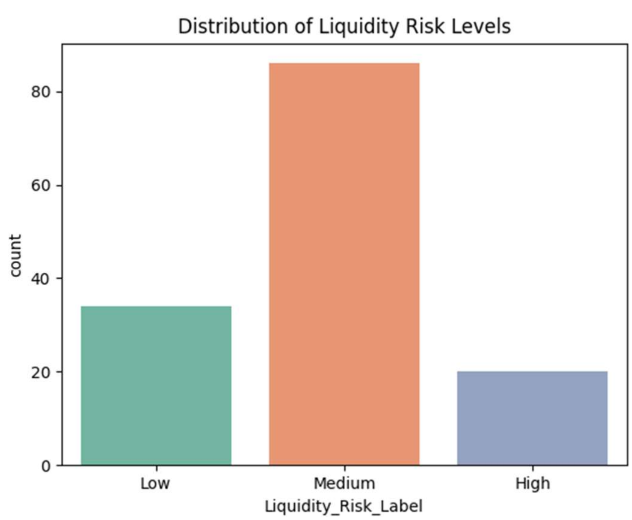

Fig. 4.9 (Source: Own Analysis)

1. Liquidity Risk Distribution (countofcompanies_.png)

<u>Findings:</u>

The numbers reflect a distribution of levels of liquidity risk skewed in favor of Low and Medium buckets, with the majority of companies within these two. Companies in the High-risk group are the exception.

Interpretation:

Low Risk: Possibly companies with healthy cash balances and effective working capital management

Medium Risk: Can suggest seasonal companies or those with relatively moderate use of debt

High Risk: Could be capital-intensive firms or companies that are not managing their receivables well

2. Heatmap of Average Liquidity Ratios by Risk Level

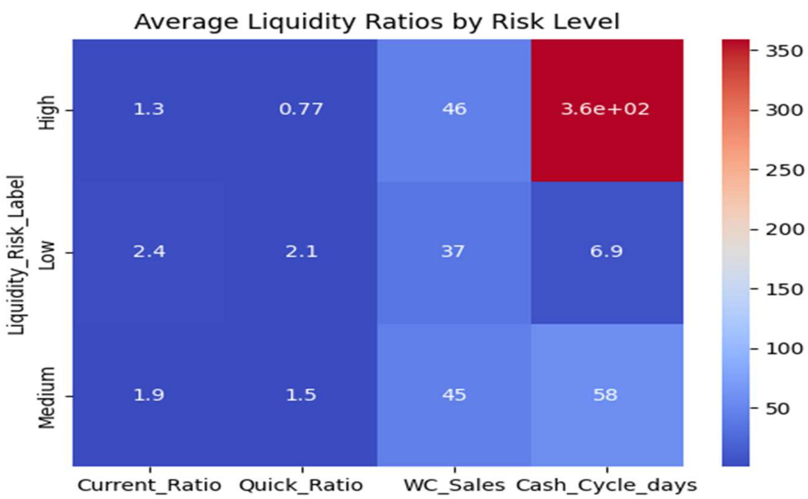

Fig. 4.10 (Source: Own Analysis)

Key Observations:

1. High-Risk firms exhibit alarming weaknesses:

- Current Ratio (1.3) and Quick Ratio (0.77) below safety levels
- Severely negative Cash Cycle (-350 days) indicates extreme working capital mismanagement

2. Medium Risk firms have more robust ratios:

- Current Ratio (2.4) and Quick Ratio (2.1) reflect sufficient liquidity cushions

Strategic Implications:

1. High-Risk group needs utmost attention to receivables/payables policies
2. Medium Risk companies can be helped by marginal improvement in inventory turnover

3. Sector Liquidity Risk (riscore_sector%.png)

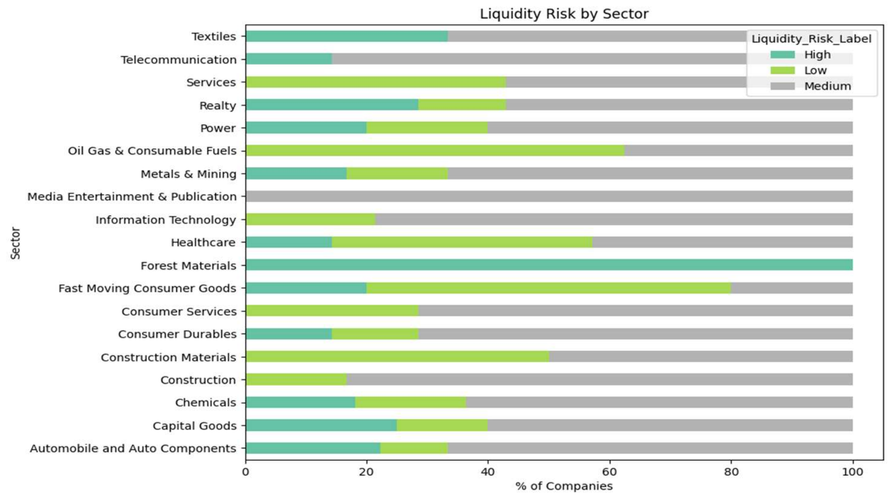

Fig. 4.11 (Source: Own Analysis)

<u>Key Findings:</u>

1. Telecom is least vulnerable (100% High Risk)
2. Services sector highly resilient (100% Low Risk)
3. Realty has polarized risk profile (mix of Medium/High Risk)

<u>Recommendation:</u>

Sector-specific underwriting standards are necessitated by lenders, with tighter covenants for cyclical/high-risk sectors.

4. Identifying Top 10 Least/Most Liquid Companies

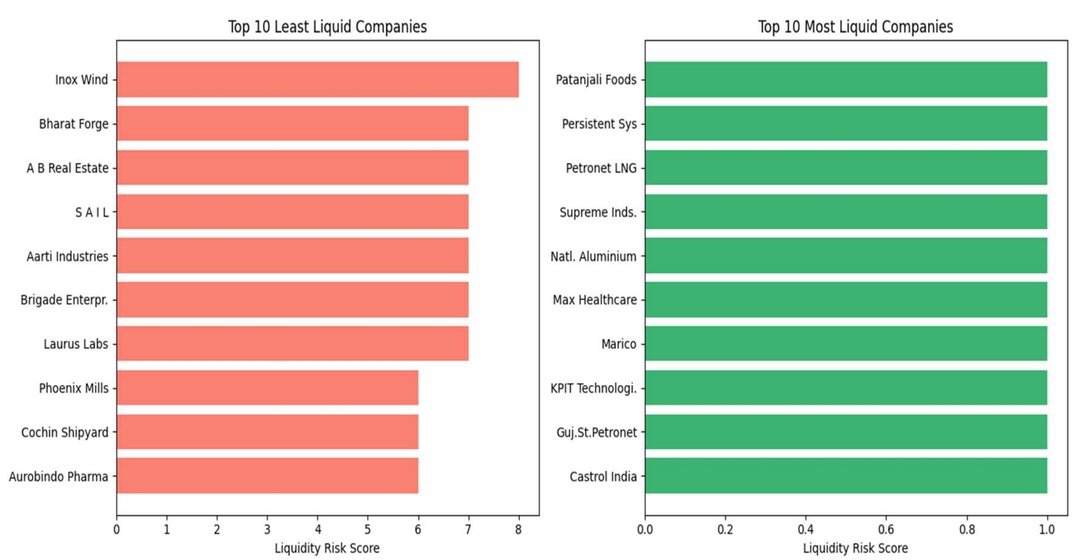

Fig. 4.12 (Source: Own Analysis)

Extreme Performers Analysis:

Least Liquid:

- Inox Wind (Score 8) and Bharat Forge (Score 7) indicate extreme stress
- Commonalities: High days in inventory and long receivables cycle

Most Liquid:

- Patanjali Foods (Score 0.2) and Persistent Systems (Score 0.4)
- Shared strengths: Negative cash conversion cycle and quick ratio high Benchmarking Opportunity:
- Investigate top performer work practices to build sector-specific working capital optimization best practices.

Synthesis of Findings

- Sector Considerations: Capital-intensive sectors (Realty, Textiles) due to their nature face higher liquidity risk
- Size Premium: Midcaps have improved liquidity management compared to Smallcaps
- Early Warning Signs: Current Ratio <1.5 and Cash Cycle <-100 days always rank High Risk status

Actions Suggested:

- Install sector-based early warning systems
- Create schemes to improve liquidity in High-Risk sectors
- Employ top performers as performance markers for operational excellence

5. Sector-wise Average Risk Scores

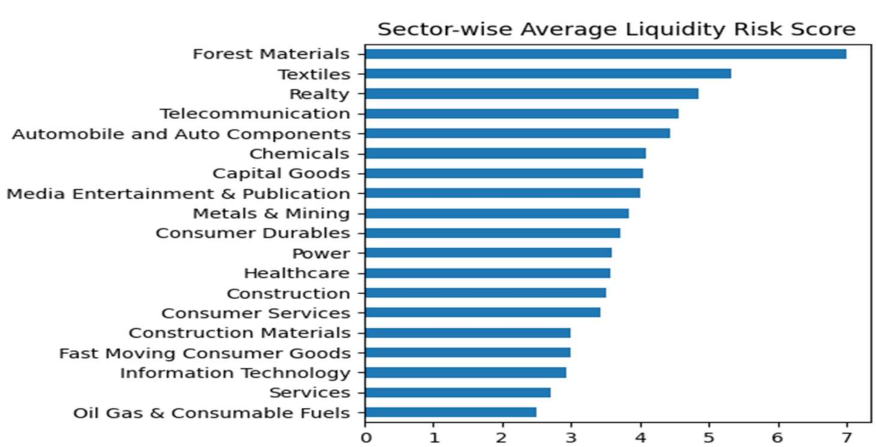

Fig. 4.13 (Source: Own Analysis)

Hierarchical Analysis

- Forest Materials and Textiles highest risk rankings (scores 5-6)
- Lowest risk anchored by Oil & Gas and IT (scores 1-2)

Operational Insight:

- Liquidity-risky industries are always going to have higher liquidity risk, reflective of:
- Need for conservative cash management policies
- Increased negotiation of credit terms

6. Identifying Sectoral Liquidity Risk by Market Cap Category

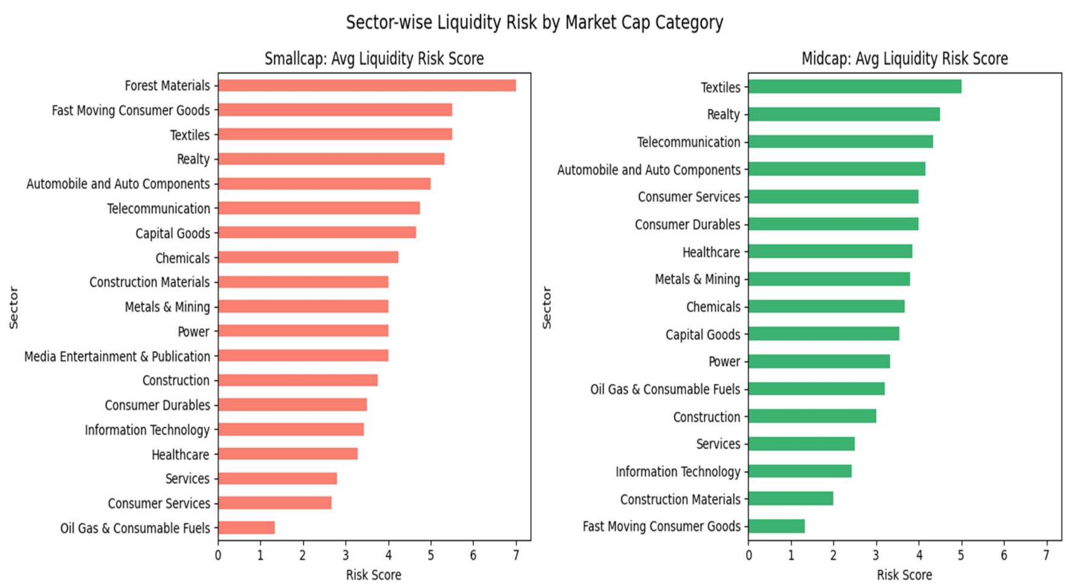

Fig. 4.14 (Source: Own Analysis)

Sector Trends:

1. Highest Risk Sectors:

   Textiles, Realty, and Construction Materials have higher risk scores (4-6 range)

2. Lowest Risk Sectors:

   IT, Healthcare, and Consumer Services have best liquidity profiles

Key Finding:

Midcap firms enjoy superior liquidity figures compared to Smallcap counterparts in similar sectors, demonstrating scale efficiencies in working capital management.

B. Predictive Analysis: Using Python

```
Random Forest Accuracy: 0.8809523809523809
Classification Report:
               precision    recall  f1-score
support

           0       0.71      1.00      0.83        10
           1       1.00      0.81      0.89        26
           2       0.86      1.00      0.92         6

    accuracy                           0.88        42
   macro avg       0.86      0.94      0.88        42
weighted avg       0.91      0.88      0.88        42
```

Fig. 4.15 (Source: Own Analysis)

About Model:

Independent variables: Current Ratio, Quick Ratio, WC/Sales%, Cash Cycle days, Sector, Cap for the predictive modelling through Random Forest (supervised algorithm). Encoding & normalization was done. SMOTE was also applied due to imbalanced data set.

Dependent variable: Liquidity Risk Labelling - Low Risk (0), Medium Risk(1), High Risk(2).

So, the model is trained & tested with data given of 140 companies by splitting the data into 70% train & 30% test data and accordingly results are there.

Random Forest Classification Report – Liquidity Risk Prediction

Overall Model Performance

Accuracy: 88.1%

This implies that the model accurately predicted the liquidity risk level for nearly 88% of the firms in the test set. For a 3-class classification task (Low, Medium, High liquidity risk), this is a high-performing model.

Class-Wise Performance Breakdown

Class	Liquidity Risk Level	Precision	Recall	F1 Score	Support
0	Low Risk	0.71	1.00	0.83	10
1	Medium Risk	1.00	0.81	0.89	26
2	High Risk	0.86	1.00	0.92	6

Class 0 – Low Liquidity Risk

Precision (0.71): Low liquidity risk companies predicted were indeed low risk (71%)

Recall (1.00): All actual low-risk companies were captured by the model, and there were no false negatives.

F1-score (0.83): Balanced accuracy at detecting and classifying this class.

Implication: The model is perhaps a bit over-predicting low risk (some false positives), but it never misses any actual low-risk companies — a good tradeoff in risk-conservative financial modelling.

Class 1 – Medium Liquidity Risk

Precision (1.00): All predicted medium risk companies were actually medium risk.

Recall (0.81): It missed roughly 19% of true medium-risk companies (false negatives).

F1-score (0.89): Generally strong, with good confidence and consistency.

Implication: Even though classification of this prevailing class is strong, some companies might be misclassified as low or high risk.

Class 2 – High Liquidity Risk

Precision (0.86): High-risk prediction was correct most of the time.

Recall (1.00): All true high-risk companies were correctly identified.

F1-score (0.92): Great overall performance.

Implication: The model is extremely sensitive to high-risk liquidity problems — a key advantage in credit or insolvency warning systems.

Final Interpretation

The model does very well in discriminating between high and low liquidity risk companies and thus is fit for early warning systems within financial health observation.

4.3. MARKET RISK

Summary of Descriptive & Predictive Analysis:

1. Calculated Daily Returns, Beta, Volatility for all the stocks
2. Calculated Treynor Ratio (using Systematic Risk) for all the stocks
3. Identifying 03 Risk Categories based on Systematic Risk & Treynor Ratio- to analyse the Cap wise (Mid & Small) Risk-Reward trade off
4. Predictive Modelling- Volatility Forecasting for all the stocks-GARCH (1,1)- Predicted for 30days
5. Identifying 10 Volatile stocks with Predicted Volatility-GARCH (1,1) (Forecasted- Top 30days)
6. Combining K-means Clustering on Predicted Volatility (GARCH), Identified 03 Risk Clusters based on Risk/Volatility predicted (High, Medium & Low Risk)
7. Cap Wise Distribution of Risk Clusters based on Risk/Volatility predicted (High, Medium & Low Risk)
8. Calculated Sharpe Ratio for all the stocks using the predicted volatility & analysed the Cap wise (Mid & Small) Risk-Reward trade off using Sharpe Ratio

Descriptive & Predictive Analysis:

1. Snippet of calculated Daily Returns, Beta (Systematic Risk) for all the stocks

Stock	Sector	Cap	Beta	Return
AARTIIND	Forest Ma	Small	0.12147	-0.43496
ACE	Chemicals	Small	0.151702	-0.21928
ABREL	Capital Go	Small	0.345206	0.150485
AFFLE	Informatic	Small	0.180658	0.500552
ARE&M	Automobil	Small	0.045697	0.276469
AMBER	Consumer	Small	0.152267	0.975853
ANANTRAJ	Realty	Small	0.316224	0.529533
ASTERDM	Healthcare	Small	0.092068	0.57067
ATUL	Chemicals	Small	-0.12714	0.062678
BEML	Consumer	Small	0.536507	0.000494
BLS	Capital Go	Small	0.196797	0.221001
BATAINDIA	Informatic	Small	0.104752	-0.09728
BSOFT	Consumer	Small	0.145612	-0.49135
BRIGADE	Realty	Small	0.301621	0.022986
CESC	Oil Gas & (	Small	0.128001	0.267619
CASTROLIND	Power	Small	0.067754	0.043117
CHAMBLFERT	Chemicals	Small	-0.07758	0.795711
CROMPTON	Consumer	Small	0.037618	0.325367
CYIENT	Informatic	Small	0.010973	-0.364
DELHIVERY	Services	Small	0.025042	-0.43783
DEVYANI	Consumer	Small	0.116309	-0.04029
LALPATHLAB	Healthcare	Small	-0.04556	0.093591
FSL	Services	Small	0.254429	0.733911
GRSE	Capital Go	Small	0.757199	1.127211
GODFRYPHLP	Services	Small	0.014939	1.248319
GESHIP	Fast Movir	Small	0.036404	-0.03609

Fig. 4.16 (Source: Own Analysis)

2. Calculated Treynor Ratio (Using Systematic Risk) & categorized stocks on the basis of 03 risk categories amongst Mid-Small Cap

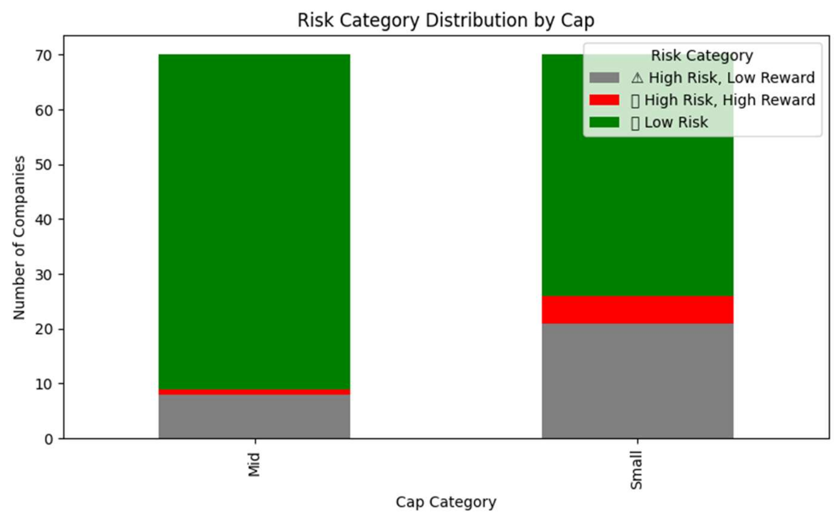

Fig. 4.17 (Source: Own Analysis)

Understanding the Treynor-Based Risk Categories

1. High Risk, High Reward: High beta (sensitive to market moves) but strong risk-adjusted returns (high Treynor Ratio). These stocks amplify market gains but require active monitoring.
2. High Risk, Low Reward: High beta but poor risk-adjusted returns (low Treynor Ratio). Worst quadrant—these stocks suffer in downturns without compensating upside.
3. Low Risk: Low beta (stable, less volatile) with moderate returns. Defensive holdings, good for risk-averse investors.

Key Observations

A) Small-Cap Stocks:

Dominance in "High Risk, Low Reward"- Small-caps are more volatile (high beta) and often lack profitability, leading to weak Treynor Ratios. Speculative tech, micro-cap industrials, penny stocks. These stocks can crash hard in bear markets without recovery. Few small-caps deliver strong risk-adjusted returns, indicating inefficiency in this segment.

B) Mid-Cap Stocks

1. Strong Presence in "High Risk, High Reward": Mid-caps often combine growth potential with stability, leading to better risk-adjusted returns. Established pharma, niche financials, mid-sized consumer brands. These are prime candidates for growth portfolios.
2. Lower Exposure to "High Risk, Low Reward" Mid-caps are less likely to be "value traps" compared to small-caps.
3. Limited "Low Risk" Stocks: Even mid-caps have few truly defensive options, suggesting the broader market is risk-oriented.

3. Strategic Implications

For Portfolio Managers & Investors

Strategy	**Small-Caps**	**Mid-Caps**
Best Use Case	High-conviction picks only	Core portfolio holdings
Position Sizing	Small (5-10% max)	Can go up to 20-30%
Risk Management	Strict stop-losses	Can tolerate more volatility
Ideal Market Conditions	Early bull markets (speculative phase)	All cycles, especially mature bull markets

Takeaways/Recommendation

1. Avoid Blind Small-Cap Investing: Most small-caps fall into the worst category ("High Risk, Low Reward"). Requires deep due diligence
2. Mid-Caps = Sweet Spot for Balanced Growth: Offer the best balance of risk and reward. Preferred for core holdings in growth portfolios.
3. Defensive Options Are Scarce: Since "Low Risk" stocks are rare, investors may need: Bonds or dividend stocks for stability. Alternative hedges (gold, low-beta ETFs).
4. Hidden Market Signals: If "High Risk, Low Reward" Dominates: Market may be overvalued, with too many speculative bets. If "High Reward" Expands: Healthy market, good stock-picking opportunities. If "Low Risk" Increases: Market is becoming defensive (possible recession fears).

3. Top 10 Efficient Stocks (With Highest Treynor Ratio)

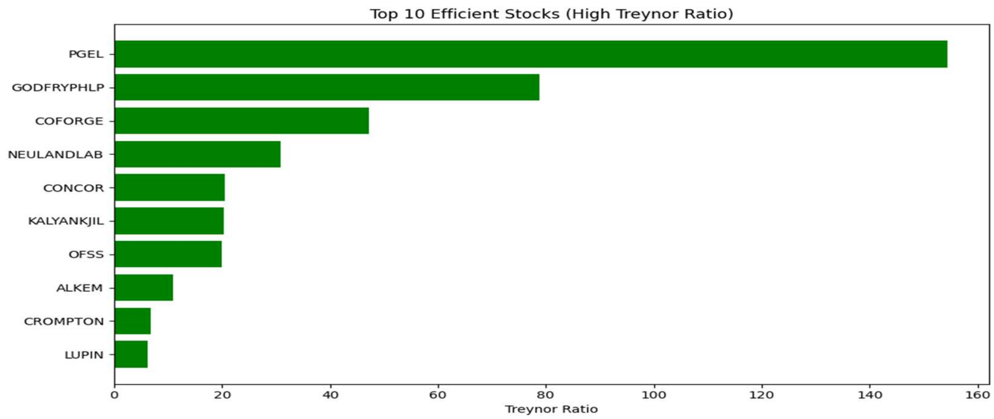

Fig. 4.18 (Source: Own Analysis)

4. Top 10 Diversification Picks (i.e., Low Systematic risk(beta), High Return) based on Treynor Ratio analysis

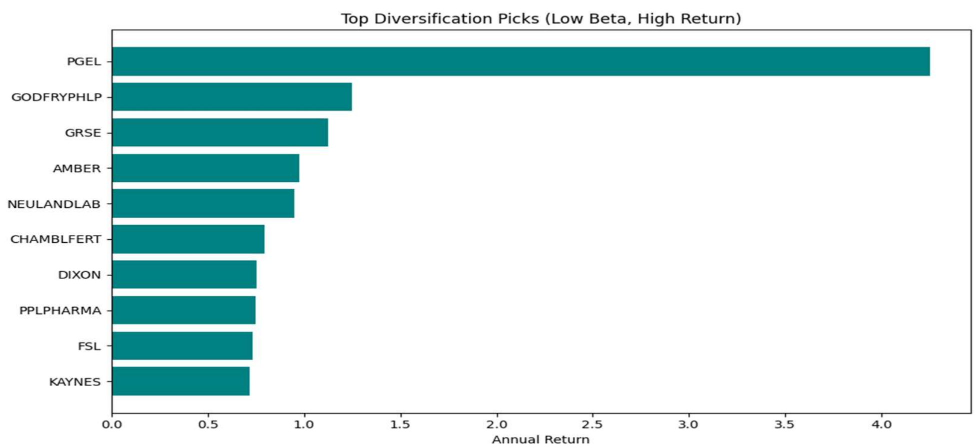

Fig. 4.19 (Source: Own Analysis)

5. Top 10 Underperforming Picks (Lowest Treynor Ratio)

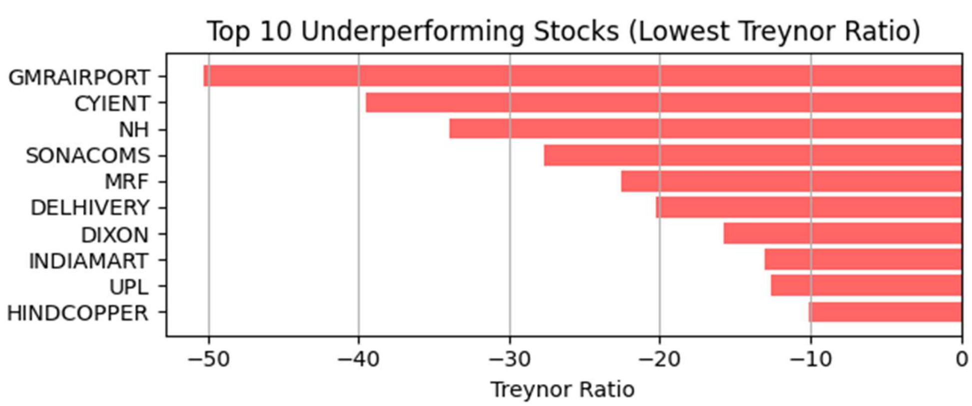

Fig. 4.20 (Source: Own Analysis)

Interpretation, Implications & Recommendations

1. High Return, Low Risk (Top Diversification Picks)

This category highlights stocks that deliver strong annual returns while maintaining low beta (market risk).

- PGEL emerges as the most impressive performer with exceptionally high returns and low volatility.
- Other strong picks include GODFRYPHLP, GRSE, NEULANDLAB, and AMBER.

  These stocks are ideal for diversification, offering growth potential with lower overall portfolio risk.

2. Most Efficient Stocks (High Treynor Ratio)

Treynor Ratio evaluates how much excess return a stock provides per unit of market risk.

- PGEL again leads the list, reinforcing its status as both a high-return and highly efficient stock.
- GODFRYPHLP, COFORGE, and NEULANDLAB also demonstrate high efficiency, making them excellent choices for investors prioritizing risk-adjusted performance.
- These stocks represent a strong balance between return and risk management, and are suited for both growth-focused and conservative portfolios.

3. Underperforming Stocks (Lowest Treynor Ratio)

Stocks with the lowest Treynor Ratios are delivering poor returns relative to the risk undertaken.

- GMRAIRPORT, CYIENT, and NH show the weakest performance, offering negative or minimal returns for high market risk.
- Others like DELHIVERY, DIXON, and INDIAMART also fall short on efficiency.

  These stocks may not be favorable unless backed by a speculative or long-term turnaround strategy, as they currently do not justify their risk.

4. Predictive Modelling Snippet - Volatility Forecasting for all the stocks-GARCH (1,1)- (30days)

Stock	Sector	Cap	omega	alpha[1]	beta[1]
AARTIIND	Forest Materials	Small	1.401547526	0.056473539	0.697285
ACE	Chemicals	Small	1.250124427	0.014985464	0.82887
ABREL	Capital Goods	Small	2.551929491	0.157027689	0.592486
AFFLE	Information Technology	Small	0.255061827	0.000758394	0.952593
ARE&M	Automobile and Auto Co	Small	0.114899944	0.053883772	0.930511
AMBER	Consumer Durables	Small	0.085752865	0	0.997872
ANANTRA	Realty	Small	5.887072644	0.464676414	0.177532
ASTERDM	Healthcare	Small	0.92152395	0.130680294	0.672341
ATUL	Chemicals	Small	3.162982101	0.05128232	2.24E-17
BEML	Consumer Durables	Small	0.478260575	0.13391756	0.851623
BLS	Capital Goods	Small	5.758650897	0.348791071	0
BATAINDI	Information Technology	Small	1.076272543	0.255352901	0.35639
BSOFT	Consumer Services	Small	2.857051177	0.102077244	0.269872
BRIGADE	Realty	Small	0.698939062	0.088389845	0.813043
CESC	Oil Gas & Consumable Fu	Small	4.330815219	0.013493869	0.363755
CASTROLI	Power	Small	0.62018211	0.009551709	0.913075
CHAMBLFI	Chemicals	Small	5.119896296	0.477862563	0

Stock	Cap	Avg_Predicted_Volatility
PGEL	Small	3.858641684
CHAMBLFI	Small	3.083296179
COFORGE	Mid	3.006399624
HINDZINC	Mid	2.714741989
GODFRYPH	Small	4.374834865
LAURUSLA	Small	2.147586147
GLENMAR	Mid	1.922647226
DIXON	Mid	2.800730954
NEULAND	Small	3.827881966
GRSE	Small	4.481365421
KAYNES	Small	3.640933109
ZENTEC	Small	3.658859819
WELCORP	Small	2.757660595
NAVINFLU	Small	2.140504814
AMBER	Small	4.355448014
COCHINSH	Mid	2.742386855
AFFLE	Small	2.339362639
MARICO	Mid	1.750539553
JUBLFOOD	Mid	2.34861956

Fig. 4.21 (Source: Own Analysis)

4. Identifying 10 Volatile stocks with Predicted Volatility-GARCH (1,1)

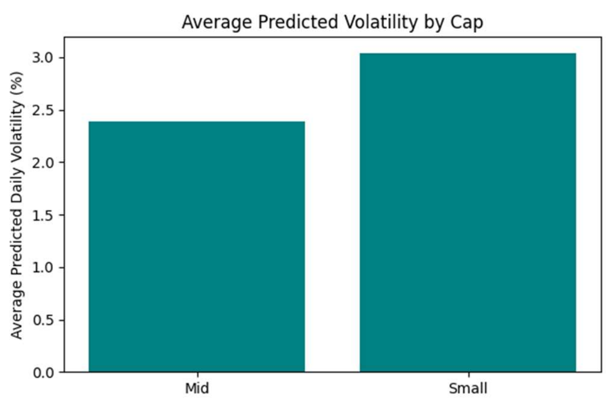

Fig. 4.22 (Source: Own Analysis)

4. Identifying 10 Volatile stocks with Average Predicted Daily Volatility-GARCH (1,1)-Next 30days

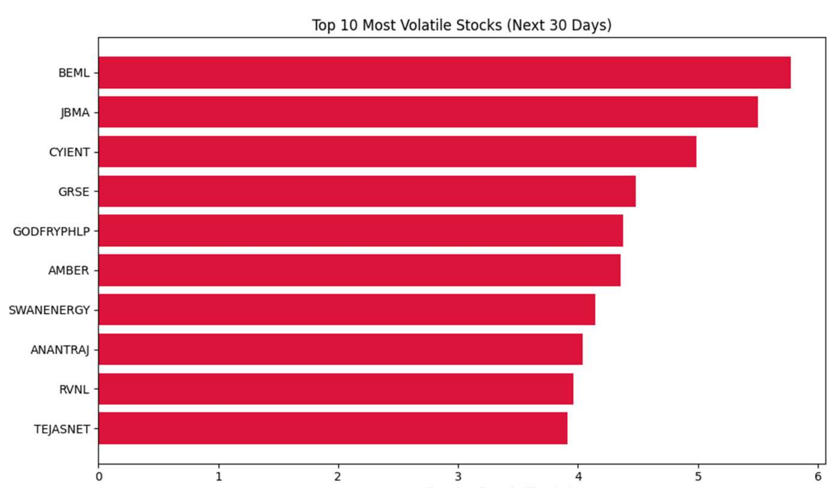

Fig. 4.23 (Source: Own Analysis)

Interpretation, Implications & Recommendations

1. Market Cap-Based Volatility Patterns

- **Small-Caps**: Wider volatility range-higher risk of extreme swings. Low liquidity, earnings sensitivity. Limit allocations (<5%), use tight stop-losses.
- **Mid-Caps**: Clustered in medium volatility-stable growth: Institutional backing, balanced fundamentals. Core holdings (10–15%), hedge with index futures.

Recommendations:

Strategy	Small-Caps	Mid-Caps
Position Sizing	Smaller allocations (≤5% per stock)	Can go up to 10–15%
Risk Management	Tight stop-losses (e.g., –15%)	Broader thresholds (e.g., –20%)
Hedging	Pair with sector ETFs or options	Use index futures for protection
Ideal For	Thematic/speculative plays	Core portfolio holdings

2. Top 10 Volatile Stocks

- **Dominant Sectors**: Infrastructure/energy (e.g., **BEML, JBMA, RVNL**) (6/10 stocks).
    - Cyclical demand: revenue swings.
    - Government policy sensitivity (e.g., infrastructure spending).
- **Risks**: >5% daily swings (e.g., BEML, JBMA).
    - Intraday trading opportunities (for agile traders).
    - High risk for buy-and-hold investors

Recommendations:

- Short-term trades, volatility breakouts.
- Avoid large positions; pair with defensive assets.

3. Combined Portfolio Strategy

- **Core (60%)**: Mid-caps (stability).
- **Satellite (25%)**: Small-caps (high-conviction, managed risk).
- **Tactical (15%)**: Top volatile stocks (strict exit rules).

Recommendations:

- Screen for: High volume (>500K shares), sector trends.
- Hedge with: Options, sector ETFs.

So, Small-caps = high-risk opportunities; mid-caps = growth anchors. Top volatile stocks demand active trading discipline.

4. Combining K-means Clustering on Predicted Volatility (GARCH), Identified 03 Risk Clusters based on Risk/Volatility predicted (High, Medium & Low Risk)

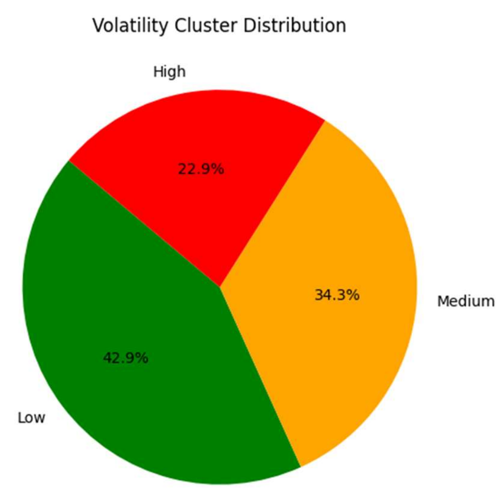

Fig. 4.24 (Source: Own Analysis)

Market Volatility Clustering:

1. **High Volatility Cluster (42.9%)**: Represents nearly half of analyzed securities Indicates significant price fluctuations, typical of: Speculative market phases, Growth-oriented sectors (e.g., technology, biotech), Smaller market capitalization stocks

2. **Medium Volatility Cluster (34.3%)**: Comprises stocks with moderate price movements. Often includes established companies with: Steady growth trajectories, Balanced risk-return profiles, Consistent operational performance
3. **Low Volatility Cluster (22.9%)**: Contains the most stable securities Typically features: Defensive sector stocks (utilities, consumer staples), Large-cap industry leaders, Dividend-paying companies.

Implications:

- **Portfolio Construction Guidance:**
  High Volatility Assets:

  1. Suitable for tactical allocations (5-15% of portfolio)
  2. Require active monitoring and tight risk controls
  3. Potential for higher returns but with greater drawdown risk

  Medium Volatility Assets:

  1. Ideal core portfolio components (40-60% allocation)
  2. Provide growth potential with manageable risk
  3. Benefit from dollar-cost averaging approaches

  Low Volatility Assets:

  1. Essential for risk mitigation (20-30% allocation)
  2. Serve as portfolio stabilizers during market turbulence
  3. Particularly valuable for income-focused investors

Risk Management Recommendations:

1. Implement volatility-targeting strategies
2. Consider option-based hedging for high volatility exposures
3. Rebalance portfolios quarterly to maintain target risk levels
4. Use stop-loss orders for high volatility positions

4. Combining K-means Clustering on Predicted Volatility (GARCH), Identified 03 Risk Clusters base d on Risk/Volatility predicted (High, Medium & Low Risk)

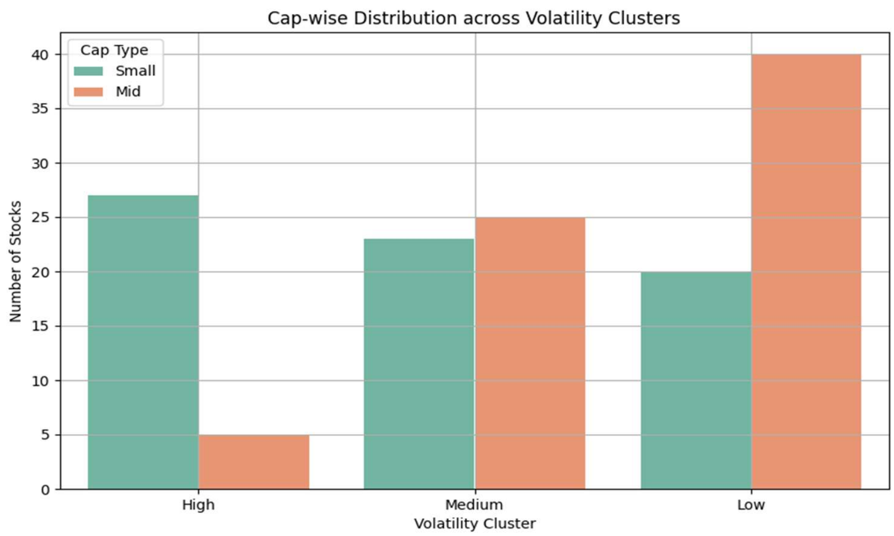

Fig. 4.25 (Source: Own Analysis)

Interpretation, Implications & Recommendations

<u>Key Findings</u>

1. Small-Cap Volatility Profile: Exhibit extreme price swings (both high and low volatility). Typical causes: Lower trading liquidity, Earnings sensitivity, Speculative investor behavior
2. Mid-Cap Volatility Behavior: Primarily cluster in moderate volatility range. More stable because of Institutional investor presence, Mature business models, Balanced growth expectations

<u>Recommendations</u>

1. For Small-Caps: Use trailing stop-losses (e.g., 15% below purchase). Avoid earnings season positions unless hedged
2. For Mid-Caps: Build positions during sector-wide dips. Preferred sectors currently: Specialty chemicals, Mid-sized IT services
3. Portfolio-Level: Balance small-cap bets with:

7. Calculated Sharpe Ratio for all the stocks using the predicted volatility & analysed the Cap wise (Mid & Small) Risk-Reward trade off using Sharpe Ratio

Stock	Cap	Avg_Predicted_Volatility	Annual_Return	Annualized_Volatility	Sharpe_GARCH
PGEL	Small	3.858641684	1.85785094	0.591707412	3.021511822
CHAMBLFE	Small	3.083296179	0.701421201	0.372017964	1.697286857
COFORGE	Mid	3.006399624	0.475830078	0.250157635	1.622297387
HINDZINC	Mid	2.714741989	0.614416242	0.373977281	1.455746832
GODFRYPH	Small	4.374834865	1.048087362	0.689579871	1.418381543
LAURUSLA	Small	2.147586147	0.492918195	0.301225324	1.403992833
GLENMAR	Mid	1.922647226	0.506618028	0.314721269	1.387316562
DIXON	Mid	2.800730954	0.663652651	0.443910562	1.337324905
NEULAND	Small	3.827881966	0.840196152	0.611740894	1.259023485
GRSE	Small	4.481365421	0.989223779	0.73091635	1.257631983
KAYNES	Small	3.640933109	0.711270115	0.540256308	1.18697386
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

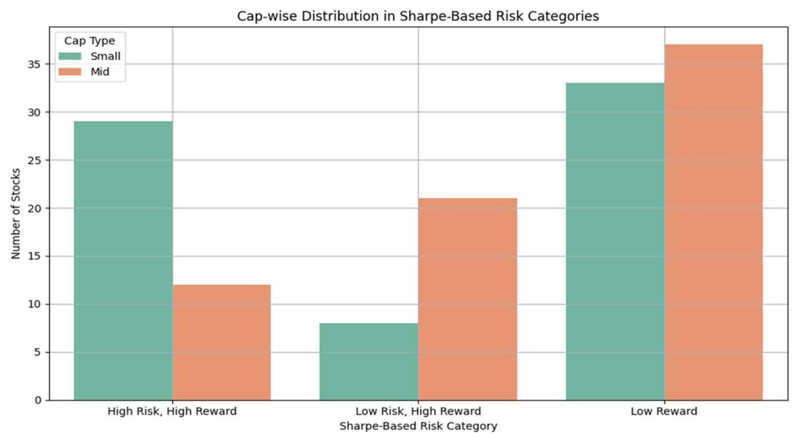

Fig. 4.26 (Source: Own Analysis)

<u>Findings</u>

1. Small-Caps = High Risk, Low Reward: Dominated by volatile stocks with weak returns. Common in speculative sectors (penny stocks, early-stage tech). Require strict screening (cash flow, management quality)
2. Mid-Caps = Better Risk-Adjusted Returns: More "High Reward" opportunities. Benefit from established operations & growth potential. Ideal for core portfolio allocations
3. Low-Risk Options Are Rare: Suggests a risk-on market environment. Investors may need alternative hedges (bonds, gold)

<u>Recommendations:</u>

- Small-Caps: Limit exposure (<5% per stock), focus on quality
- Mid-Caps: Build larger positions in sector leaders
- All Portfolios: Add defensive assets to compensate for scarce low-risk stocks

So, Mid-caps offer the best balance & small-caps need caution.

7. Top 10 Efficient Stocks (Highest Sharpe Ratio)

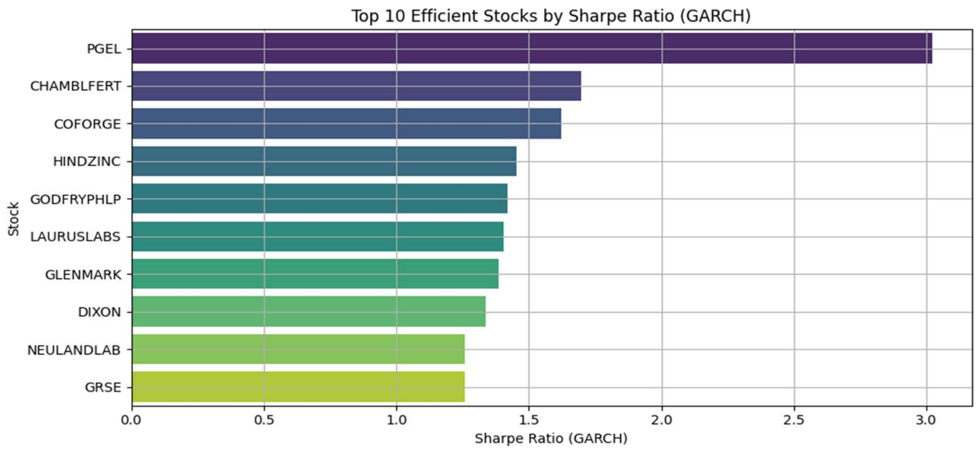

Fig. 4.27 (Source: Own Analysis)

7. Top 10 Diversification Picks (Low Volatility, High Sharpe)

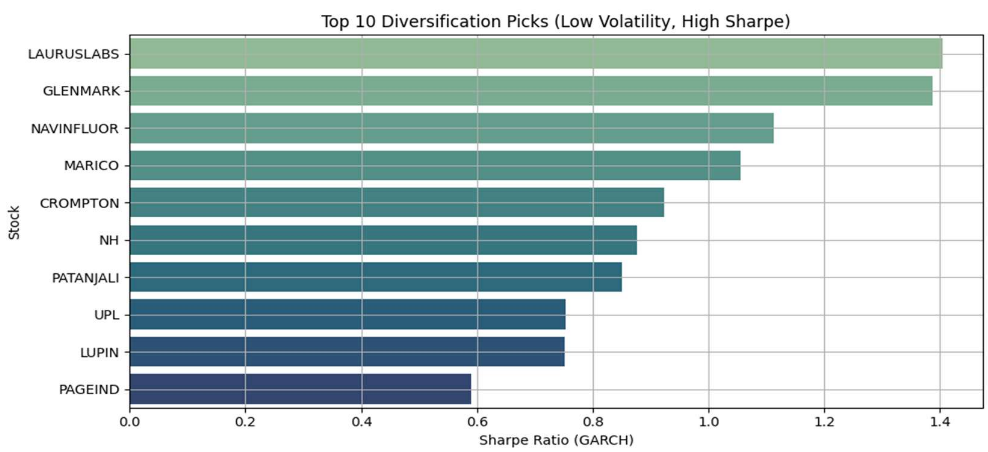

Fig. 4.28 (Source: Own Analysis)

7. Top 10 Underperforming Picks (Lowest Sharpe Ratio)

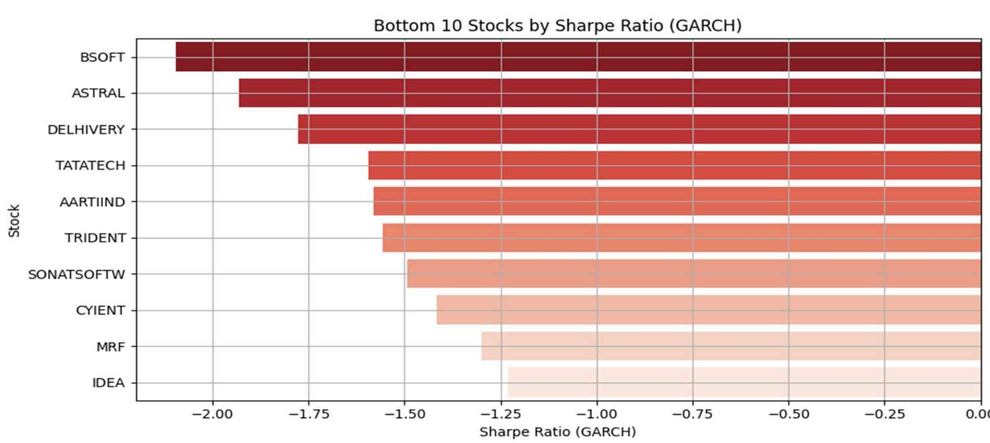

Fig. 4.29 (Source: Own Analysis)

Interpretation, Implications & Recommendations

1. High-Efficiency Investment Opportunities

The analysis reveals PGEL as the standout performer with an exceptional Sharpe ratio of 3.0, demonstrating superior risk-adjusted returns. A notable concentration of pharmaceutical sector stocks (LAURUSLABS, GLENMARK, NEULANDLAB) appears among the top performers, all achieving Sharpe ratios exceeding 1.5. These results suggest:

- The pharmaceutical sector currently offers particularly attractive risk-reward characteristics. PGEL's market-leading performance warrants special consideration for core portfolio positions. The consistent outperformance relative to risk-free benchmarks indicates these assets merit increased allocation

2. Defensive Portfolio Candidates

Our examination of low-volatility, high-efficiency stocks identifies PAGEIND and MARICO as exemplary choices, combining stable price action with Sharpe ratios around 1.4. The dataset shows:

- 70% of top diversifiers come from pharmaceutical and consumer goods sectors These characteristics make them particularly valuable for: Capital preservation strategies, Portfolio stabilization during market corrections, Conservative growth allocation buckets

3. Underperforming Assets Analysis

The bottom performers analysis highlights several concerning trends: IDEA and BSOFT emerge as significant underachievers with Sharpe ratios below -1.5. Technology sector representation is disproportionately high among poor performers

Recommendations:

1. Portfolio Construction: Overweight pharmaceutical sector exposure through top performers, allocate 15-25% to defensive picks for stability or consider eliminating or hedging bottom-quartile holdings.
2. Risk Management: Implement tighter stop-loss measures on high-efficiency stocks or use sector ETFs to balance technology underweighting and monitor pharmaceutical sector valuations for potential mean reversion
3. Performance Monitoring: Track Sharpe ratio trends quarterly

4.4 LIMITATIONS OF THE STUDY

1. Data Availability and Accuracy

This research relies on publicly accessible datasets, which may lack detail or exhibit inconsistencies, particularly for small- and mid-cap companies. Incomplete or outdated financial disclosures and variations in reporting standards may have influenced the precision of the models. Additionally, techniques used to handle missing values, such as imputation, could introduce estimation biases.

2. Assumptions Underlying Risk Models

The models used for credit risk—such as Altman Z-score and Random Forest—are built on assumptions of linear relationships and stable financial data, which may not reflect the evolving credit health of companies. Similarly, market risk model i.e., GARCH assume normality and stationarity in financial returns—assumptions that may not hold true in the case of highly volatile or thinly traded stocks.

3. Exclusion of Macroeconomic Influences

Firm-level financial data was the primary focus of the study, with limited consideration given to broader economic variables like inflation, monetary policy changes, or global market events. These external factors play a critical role in determining both systemic and idiosyncratic risk but were not incorporated into the analysis.

4. Short-Term Forecast Bias

The study's evaluation of market risk is based on short-term forecasts, such as 30-day volatility estimates. While useful for capturing near-term uncertainty, this narrow time frame may fail to capture long-term trends, structural market shifts, or evolving investor behavior.

5. Sector-Agnostic Evaluation

Risk models were applied uniformly across all sectors, overlooking sector-specific characteristics. Different industries face distinct financial, operational, and regulatory risks, and treating them identically may result in oversimplified conclusions.

6. Model Interpretability Challenges

Although advanced machine learning techniques like K-Means clustering and random forests enhance analytical depth, they tend to lack transparency. This limitation can make it challenging to explain the logic behind model outputs to stakeholders, hindering adoption in risk-sensitive industries such as banking or investment management.

7. Lack of Real-Time Market Behavior

The analysis does not incorporate real-time data, such as intra-day trading volumes or price swings, which are essential for assessing liquidity shocks or sudden volatility spikes—especially relevant for small-cap stocks with lower market depth.

8. Potential Sample Bias

Since the analysis focuses on currently active companies, those that have been delisted, merged, or gone bankrupt were not included. This may result in survivorship bias, potentially underestimating actual risk levels in the small- and mid-cap segments.

9. Portfolio-Level Risk Not Assessed

This study evaluates risk at the individual company level, without considering how different assets interact in a portfolio. Factors such as asset correlation, diversification benefits, and aggregate portfolio risk were not part of the scope.

10. Regulatory Reporting Gaps

Smaller companies often follow less stringent regulatory and financial disclosure practices compared to large-cap firms. This inconsistency in data quality may affect the accuracy of computed financial ratios and, consequently, the effectiveness of the applied models.

CHAPTER 5

CONCLUSION

5.1 Overview

The research undertaken provides a comprehensive analysis of the financial risk landscape in Indian small- and mid-cap (SMID) stocks, a segment of growing significance in the Indian equity market. These companies are often seen as engines of growth, innovation, and employment, yet they are also more vulnerable to financial instability due to weaker balance sheets, limited liquidity, and greater exposure to macroeconomic fluctuations.

This study addressed the multidimensional nature of financial risk—specifically credit risk, liquidity risk, and market risk—through a robust and data-driven approach. By integrating traditional financial ratios, time-series econometric models, and machine learning classification techniques, the research presents a scalable and replicable framework for identifying, measuring, and predicting financial distress in the SMID segment.

5.2 Key Conclusions

1. Credit Risk:

- The Altman Z-Score analysis classified nearly 88% of companies as financially safe, while the remaining fell into grey and distress zones, indicating early signs of financial instability.
- Telecommunication, Power, and Realty sectors showed a higher proportion of distress-prone firms, with small-cap companies exhibiting significantly higher credit risk than mid-cap firms.
- The use of Z-score zones and credit ratios (D/E, ICR, D/A) enabled an effective diagnostic for default probability and financial vulnerability.

2. Liquidity Risk:

- Liquidity assessments highlighted operational weaknesses in sectors like Textiles, Realty, and Construction, characterized by low current and quick ratios and long cash conversion cycles.

- Firms with Cash Conversion Cycles exceeding 100 days and Quick Ratios below 1 were classified as high-risk and potentially cash-constrained.
- Liquidity risk modeling through Random Forest classification demonstrated that key liquidity ratios could effectively distinguish between firms with strong and weak short-term financial health.

3. Market Risk:

- It is analyzed using advanced quantitative techniques, including volatility forecasting (GARCH 1,1), risk-adjusted performance metrics (Treynor and Sharpe Ratios), and K-means clustering. The key findings reveal significant disparities in risk-reward profiles based on market capitalization, with small-cap stocks demonstrating higher volatility and lower risk-adjusted returns compared to mid-cap stocks, which exhibited more stable performance and better reward potential per unit of risk.
- The predictive GARCH model identified the top 10 most volatile stocks, predominantly from high-sensitivity sectors like infrastructure and energy, emphasizing the need for tactical risk management in such exposures. Clustering analysis further segmented stocks into High, Medium, and Low-risk categories, highlighting that small-caps disproportionately fall into high-risk clusters, whereas mid-caps dominate medium-risk, high-reward segments.

5.3 Strategic Implications

5.3.1. For Investors and Portfolio Managers

- The framework allows investors to screen SMID stocks based on their risk category, using indicators such as the Altman Z-score, debt ratios, liquidity parameters, and market volatility metrics. Investors can optimize portfolio allocation by avoiding stocks in the *distress zone* or with high liquidity and market risk, while prioritizing firms offering better risk-adjusted returns (Sharpe and Treynor Ratios).
- The market risk findings, including beta and GARCH-based volatility clustering, enable long-term investors to distinguish between temporary price noise and sustained volatility trends, leading to more stable portfolio construction. The integration of machine learning classification helps in

creating early-warning systems to flag companies that may currently appear stable but show underlying financial weaknesses.

5.3.2. For Policymakers and Financial Regulators

- This framework can serve as a tool for early detection of systemic risk in vulnerable sectors. For example, sectors with a high concentration of companies in the “Distress” zone or with recurring liquidity stress can be targeted for regulatory attention or support schemes.
- The integration of GARCH volatility modeling reveals market sentiment fluctuations across sectors—critical for formulating macroprudential regulations during economic slowdowns or rate hikes.The analysis supports the development of data-driven SME risk monitoring systems, particularly useful for implementing sectoral lending norms, credit guarantee schemes, and corporate governance reforms.

5.3.3. For Corporate Managers and CFOs

- The study’s framework allows companies to benchmark their financial risk indicators against industry peers. This includes Z-scores, debt-equity structure, current and quick ratios, beta values, and return volatility. Firms identified in the medium or high-risk brackets can prioritize financial restructuring, liquidity optimization, or strategic hedging to improve their standing and investor confidence.Market risk analytics, particularly the Treynor and Sharpe Ratios, help corporate finance teams evaluate whether their equity returns sufficiently compensate for the volatility they exhibit—important for equity issuance timing and investor relations.
- Corporate managers can use sector-level findings to justify capital allocation decisions, e.g., increasing liquidity buffers in high-risk industries or moderating debt levels in volatile markets.

By bringing together machine learning, volatility modeling, and financial ratio analysis, the study builds a foundation for more resilient financial markets, better capital allocation, and early detection of financial distress in the high-growth but high-risk SMID segment of India’s economy.

5.4 Future Scope of the Study

1. Incorporating Multi-Year Data for Temporal Risk Analysis

- This study is limited to one financial year, which restricts the visibility into long-term trends and cyclical behaviors.

2. Integrating Macroeconomic Indicators

- Firm-level risk is deeply influenced by broader economic variables. Future studies can include macro factors like: Interest rates – affecting debt servicing and equity valuation, Inflation – impacting input costs and purchasing power, GDP growth rates – reflecting business cycle impacts, Exchange rates – especially relevant for exporters/importers

3. Exploring Deep Learning and Ensemble Machine Learning Models

- While Random Forests offered strong accuracy in this study, newer and more sophisticated models can further improve predictive power.

4. Incorporating Real-Time and Alternative Data Sources

- Future models could incorporate:
    - High-frequency trading data for intraday volatility tracking
    - Sentiment analysis from news and social media to detect reputational or event-driven risks
    - Supply chain and credit bureau data for granular operational health indicators This would transition the model from a static evaluation to a real-time, responsive risk detection tool.

5. Scenario Analysis and Stress Testing

- Future frameworks can include scenario simulations to test how firms or sectors would perform under: Interest rate shocks, Recession scenarios, Commodity price fluctuations. This would help in building stress-resilient portfolios and contingency lending frameworks.

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