ST JOSEPH'S INSTITUTE OF MANAGEMENT

Primrose road, Bangalore 560 025

Study on Leveraging the Magic Formula: Building an Optimized Portfolio based on Nifty 200 by Hedge Equities

Project Report submitted in partial fulfilment of the requirements for the award of The Post Graduate Diploma in Management

(A TWO-YEAR FULL-TIME PROGRAM IN MANAGEMENT)

Submitted By

Akhil E A

Roll No. 2024023

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Certificate

This is to certify that the project report entitled: "**Study on Leveraging the Magic Formula: Building an Optimized Portfolio based on Nifty 200**." is an authentic record of the project work carried out by Mr. Akhil E A (Reg No 2024023), in partial fulfilment of the requirements for the **award of The Post Graduate Diploma in Management**.

Prof. / Dr. Ravi Darshini

Faculty Guide

Rev. (Dr) Roshan David Pereira SJ

Director

Hedge Equities
invest with an edge

17/06/2025

OFFLINE INTERNSHIP COMPLETION CERTIFICATE

This is to certify that **Mr. AKHIL E A** (Registration No: 2024023) (Hedge ID - HSAE007501) from **ST JOSEPH'S INSTITUTE OF MANAGEMENT, BANGLORE** has successfully completed his Internship program at Hedge Equities Ltd., Cochin from 07/04/2025 to 07/06/2025 in the topic **"WEALTH MANAGEMENT"**. During the Internship program, he was exposed to the various activities of our Research/Finance Department.

During the Internship program, AKHIL E A demonstrated problem solving and analytical skills. His performance exceeded expectations, and he was able to complete the program successfully on time.

We at Hedge Equities Ltd., wish him all the very best in his future endeavors.

For Hedge Equities Ltd.

HEDGE EQUITIES LTD. KOCHI

SCHOOL OF APPLIED ECONOMICS LIMITED HEDGE

Authorised Signatory

DECLARATION

I hereby declare that the project report entitled "**Study on Leveraging the Magic Formula: Building an Optimized Portfolio based on Nifty 200**" has been prepared by me during the period from 07 April 2025 to 07 June 2025 under the guidance of Mr. Ashwin Reghunath and Mr. Jaison Varghese Philip, Research Analyst, Hedge Group of Companies and Prof. Ravi Darshini Faculty Member, St Joseph's Institute of Management, Bangalore

I also declare that this project has not been submitted nor shall it be submitted in future to any other University or Institution for the award of any other Degree or diploma.

Date

Signature

Akhil E A

Acknowledgement

I take this opportunity to thank all people who all have made me sail through successfully my internship programme with a project at Hedge Group of Companies. I would like to express my deep sense of gratitude towards all the persons who helped me through their guidance and cooperation.

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Executive Summary

This study, conducted during an internship with Hedge Equities in 2025, aimed to develop a systematic investment strategy by integrating Joel Greenblatt's Magic Formula with Markowitz Modern Portfolio Theory (MPT) to construct an optimized portfolio from the Nifty 200 Index. The objective was to achieve superior risk-adjusted returns over the study period, May 12, 2022, to May 13, 2025, a dynamic phase in the Indian equity market marked by post-COVID recovery and sector-specific growth.

The methodology involved two key steps: stock selection and portfolio optimization. Using the Magic Formula, stocks were screened based on high Earnings Yield (>7%), high Return on Invested Capital (>15%), and low Price-to-Earnings ratio (<20) and excluding finance and utility stocks resulting in the selection of nine stocks: NMDC, Vedanta, Tata Motors, National Aluminium, Indus Towers, HeroMotocorp, Hindustan Zinc, ACC, and Dr Reddy's Labs. Historical adjusted closing prices were sourced from Yahoo Finance, covering 756 trading days (reduced to 740 after cleaning). MPT was then applied using a Python script to optimize portfolio weights, maximizing the Sharpe Ratio by balancing expected returns and volatility.

The optimized portfolio achieved an annual return of 26.84%, volatility of 17.87%, and a Sharpe Ratio of 1.1659 (with a risk-free rate of 6%). Key findings include the portfolio's effective risk management, driven by diversification benefits from moderate correlations (e.g., ACC with Indus Towers at 0.4358), though stocks like ACC (-0.48% return) detracted from overall returns. The study validates the effectiveness of combining the Magic Formula with MPT in the Indian market, supporting prior research by Preet et al. (2021) and Singh & Kaur (2013).

Recommendations for Hedge Equities include adopting this methodology for client portfolios to enhance risk-adjusted returns, while excluding underperforming stocks in future optimizations. Future research should test the strategy over different time horizons (e.g., 1-year, 5-year) to assess adaptability. This approach offers Hedge Equities a replicable, data-driven framework to meet the growing demand for effective investment strategies in India's expanding financial mark

Chapter One: Industry & Company Overview

Global Scenario of the Financial Services Industry

The global financial services industry is a critical pillar of the world economy, facilitating capital allocation, risk management, and economic growth. It encompasses a wide range of sectors, including banking, insurance, wealth management, asset management, stock broking, and investment advisory services. According to the International Monetary Fund (IMF), the financial services sector contributes approximately 20% to global GDP, underscoring its economic significance. As of 2025, the industry is undergoing a transformative phase, driven by technological innovation, regulatory changes, and evolving consumer expectations.

The global wealth management market is projected to reach $2.6 trillion by 2026, growing at a compound annual growth rate (CAGR) of 7.5% from 2021 to 2026, as reported by Mordor Intelligence. This growth is fueled by rising disposable incomes, increasing financial literacy, and a growing demand for personalized investment solutions. High-net-worth individuals (HNWIs) and retail investors alike are seeking tailored financial advice, prompting wealth management firms to expand their offerings. For instance, firms like UBS and Morgan Stanley have reported significant growth in their wealth management divisions, with UBS managing $3.2 trillion in assets under management (AUM) as of 2024, according to their annual reports.

Technological advancements have reshaped the industry, with fintech innovations such as robo-advisors, artificial intelligence (AI)-driven analytics, and blockchain-based platforms revolutionizing service delivery. Robo-advisors, for example, have democratized access to wealth management by offering low-cost, automated investment solutions. Companies like Betterment and Wealthfront have attracted millions of users globally, managing over $50 billion in combined AUM as of 2024. Blockchain technology has also gained traction, enhancing transparency and security in transactions, particularly in cross-border payments and asset management. The adoption of digital wallets and mobile banking apps has further accelerated financial inclusion, with Statista reporting that over 60% of global transactions were conducted digitally in 2024.

Regulatory changes have played a significant role in shaping the industry. Post the 2008 financial crisis, global regulators introduced stringent measures to enhance financial stability, such as the Basel III framework, which increased capital requirements for banks. More recently, regulations like the European Union's General Data Protection Regulation (GDPR) and the U.S. SEC's Regulation Best Interest (Reg BI) have emphasized consumer protection and transparency in financial advice. These regulations have compelled firms to invest in compliance infrastructure, with global spending on regulatory technology (RegTech) reaching $12 billion in 2024, according to a report by Deloitte.

Despite its growth, the industry faces challenges, including cybersecurity risks, geopolitical uncertainties, and market volatility. The increasing reliance on digital platforms has heightened the risk of cyberattacks, with the financial sector being the most targeted industry, accounting for 25% of global cyber incidents in 2024, according to IBM Security. Geopolitical tensions, such as trade disputes and sanctions, have also impacted cross-border investments, while market volatility, driven by inflationary pressures and interest rate hikes, has tested the resilience of investment portfolios. Nevertheless, the global financial services industry remains robust, adapting to these challenges through innovation and strategic diversification.

Indian Scenario of the Financial Services Industry

India's financial services industry is a dynamic and rapidly growing sector, playing a pivotal role in the country's economic development and financial inclusion. The industry encompasses banking, insurance, mutual funds, stock broking, wealth management, and investment advisory services, catering to a diverse population of over 1.4 billion. According to the India Brand Equity Foundation (IBEF), the sector is expected to reach $480 billion by 2025, growing at a CAGR of 10.5% from 2020 to 2025. This growth is driven by economic liberalization, technological advancements, increasing financial literacy, and a burgeoning middle class with rising disposable incomes.

The Indian stock market, managed by the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE), is a critical component of the financial services industry, providing a platform for companies to raise capital and for investors to participate in economic growth. The NSE, the largest stock exchange in India by trading volume, hosts the Nifty indices, including the Nifty 200, which represents the top 200 companies listed on the exchange. The sector's growth is evidenced by significant milestones, such as the mutual fund industry's assets under management (AUM) increasing from Rs. 9.16 trillion (US$110.63 billion) in 2014 to Rs. 64.97 trillion (US$780.70 billion) in July 2024, a nearly sixfold increase, as reported by IBEF. The insurance sector is projected to reach US$250 billion by 2025, with an additional US$78 billion in life insurance premiums expected between 2020 and 2030.

Government initiatives have been instrumental in fostering the industry's growth. The relaxation of foreign direct investment (FDI) rules in the insurance sector from 49% to 100% under the Union Budget 2025 has attracted global players, fostering joint ventures and enhancing market competitiveness. The Digital India initiative has accelerated the adoption of digital financial services, with over 2,100 fintech companies positioning India as a leading digital market. According to IBEF, the fintech sector alone is expected to reach $150 billion by 2025, driven by mobile banking, digital wallets, and payment platforms like UPI, which recorded over 100 billion transactions in 2024, as per the National Payments Corporation of India (NPCI).

Sector-specific growth drivers further highlight the industry's potential. The banking sector has seen robust growth, with total credit extended by banks reaching Rs. 164.98 trillion (US$1.98 trillion) as of July 2024, a 12.3% increase year-on-year, according to the Reserve Bank of India (RBI). The rise of retail investors in the stock market is another notable trend, with the number of demat accounts increasing to over 120 million by March 2024, as reported by the Central Depository Services Limited (CDSL). This surge reflects growing investor confidence and financial awareness, particularly among younger demographics, with 60% of new investors aged between 25 and 35, according to a SEBI survey.

The wealth management segment, though smaller, is gaining traction, driven by the increasing number of high-net-worth individuals (HNWIs) and retail investors seeking professional financial advice. India's HNWI population grew by 5.8% in 2024, reaching 3.3 lakh individuals, with combined wealth of $1.3 trillion, as per the 2024 Capgemini World Wealth Report. This growth has spurred demand for personalized investment solutions, benefiting firms like Hedge Equities, which focus on retail and mid-tier investors. However, the sector faces challenges such as regulatory compliance, market volatility, and the need for robust cybersecurity measures, given the rise in digital transactions.

Overview of the Nifty 200 Index

The Nifty 200 Index, launched by the NSE, is a broad-based index that represents the performance of the top 200 companies listed on the exchange, based on market capitalization. It includes both large-cap and mid-cap companies, providing a comprehensive view of the Indian equity market. As of March 28, 2025, the Nifty 200 Index accounts for approximately 79.90% of the free float market capitalization of the stocks listed on the NSE, making it a significant benchmark for the Indian stock market, according to Visual Capitalist. The index is constructed using the free-float market capitalization methodology, which considers only the portion of shares available for trading in the public market, ensuring that it reflects the actual tradable value of the companies.

The Nifty 200 Index is composed of companies across various sectors, including banking, information technology, pharmaceuticals, metals, automotive, and consumer goods, offering a balanced representation of the Indian economy. As of March 2025, the top sectors by weight in the Nifty 200 include financial services (30%), IT (15%), and consumer goods (12%), according to NSE data. The index's constituents represent approximately 63.97% of the total traded value of all stocks on the NSE over the last six months ending March 2025, underscoring its significance in capturing market dynamics.

The Nifty 200 Index is widely used by investors, fund managers, and researchers for various purposes, including benchmarking portfolio performance, creating index funds and exchange-traded funds (ETFs), and analyzing market trends. The index's broad coverage makes it particularly useful for investors seeking exposure to a diversified set of Indian companies across different sectors and market capitalizations. It also serves as a foundation for derivative products, such as futures and options, which are actively traded on the NSE, enhancing market liquidity and investor participation.

Players in the Industry Along with Market Shares

The Indian financial services industry is highly competitive, featuring a mix of public sector, private sector, and foreign players. In the wealth management segment, key players include:

Institution	Description	Market Position
HDFC Bank	One of India's largest private sector banks, offering comprehensive wealth management services.	Holds 10.8% of mutual fund AUM as of March 2024 (AMFI).
ICICI Bank	A major private sector bank with a strong focus on wealth management solutions.	10.2% share in life insurance market (IRDAI, 2024).
Kotak Mahindra Bank	Renowned for its wealth management and investment advisory services.	Significant presence in HNWI segment, managing $50 billion in AUM (Kotak Wealth Report 2024).
Aditya Birla Capital	Provides wealth management, insurance, and asset management services.	Manages Rs. 4.5 trillion in AUM across its businesses (Aditya Birla Capital, 2024).
Hedge Equities	A Kerala-based firm focusing on retail and mid-tier investors, emphasizing financial literacy.	Manages Rs. 2,200 crores for over 4,000 families (Hedge Equities, 2024).

The wealth management sector in India is dominated by large banks and financial conglomerates, which leverage their extensive branch networks, digital platforms, and brand recognition to attract HNWIs and institutional clients. HDFC Bank, for instance, has expanded its wealth management offerings through its merger with HDFC Ltd., becoming one of the largest wealth managers in India, with a focus on both HNWIs and retail investors. ICICI Bank has a strong foothold in the life insurance market through its subsidiary ICICI Prudential Life Insurance, which caters to wealth preservation needs. Kotak Mahindra Bank, through its wealth management arm Kotak

Wealth, has positioned itself as a leader in the HNWI segment, offering bespoke investment solutions and family office services.

Smaller firms like Hedge Equities compete by targeting niche markets, particularly retail and mid-tier investors in regions like Kerala, where financial literacy is still developing. These firms differentiate themselves through personalized services, educational initiatives, and a focus on underserved demographics. However, they face challenges such as limited scale, competition from larger players with greater resources, and the need to comply with stringent regulatory requirements, such as SEBI's enhanced disclosure norms for investment advisors introduced in 2024.

Market dynamics are also influenced by the rise of fintech companies, which have disrupted traditional wealth management models. Firms like Zerodha and Groww have gained significant traction among retail investors, with Zerodha reporting over 10 million active users and Rs. 5 trillion in broking AUM as of 2024, according to its annual report. These platforms offer low-cost trading and investment advisory services, posing a competitive threat to traditional wealth managers. Additionally, global players like Standard Chartered and Barclays have entered the Indian market, targeting the growing HNWI population, further intensifying competition.

Company Overview: Hedge Equities

Hedge Equities is a wealth management firm based in Kochi, Kerala, India, founded by Alex K. Babu in 2008 (Hedge Equities). The company was established with a mission to make wealth management accessible to all, not just the affluent, emphasizing financial education and personalized investment solutions. Hedge Equities operates under the broader Hedge Group, which includes subsidiaries focused on financial services and education.

Since its inception, Hedge Equities has grown steadily, managing assets worth over Rs 2,200 crores for more than 4,000 families as of 2024, according to its official website. The firm provides a range of services, including wealth management, stock broking, and investment advisory, catering primarily to retail and mid-tier investors. Hedge Equities is known for its client-centric approach, aiming to empower investors through financial literacy initiatives like the Hedge School of Applied Economics, which offers educational programs on investing and personal finance.

The firm has expanded its presence beyond Kerala, with branches in major cities like Mumbai, Bangalore, and Chennai, focusing on delivering value-driven investment solutions. Hedge Equities is increasingly adopting technology to enhance its services, aligning with industry trends and positioning itself as a competitive player in the Indian wealth management landscape.

Significance of the Study

This study, conducted as part of an internship with Hedge Equities' quant research team, aims to develop a systematic approach to portfolio construction that combines the Magic Formula for stock selection with Modern Portfolio Theory (MPT) for optimization. By applying this hybrid methodology to the Nifty 200 Index, the study seeks to achieve superior risk-adjusted returns, providing a practical framework for Hedge Equities to enhance its investment strategies. The study period, May 12, 2022, to May 13, 2025, captures a dynamic phase in the Indian market, including post-COVID economic recovery, inflationary pressures, and sector-specific growth, ensuring the findings are relevant and actionable.

The significance of the study lies in its alignment with industry trends and Hedge Equities' strategic objectives. The Indian financial services industry is increasingly shifting toward quantitative and data-driven investment strategies, with firms adopting advanced techniques like MPT to optimize portfolios and manage risk. The rise of retail investors, as evidenced by the surge in demat accounts to over 120 million by March 2024, underscores the need for accessible and effective investment solutions, a core focus of Hedge Equities. By integrating the Magic Formula—a proven value investing strategy—with MPT, the study addresses the firm's goal of delivering superior risk-adjusted returns, enhancing its competitive position in a crowded market.

The study also supports Hedge Equities' mission to empower retail and mid-tier investors through education and innovation. The firm's emphasis on financial literacy, through initiatives like the Hedge School of Applied Economics, aligns with the study's objective of developing a replicable framework that clients can understand and trust. This study aims to construct a portfolio using the Magic Formula and Modern Portfolio Theory (MPT) to maximize the Sharpe Ratio—demonstrates the potential of this hybrid approach to deliver value, offering a blueprint for the firm to scale its offerings and attract new clients.

Furthermore, the study contributes to the broader discourse on portfolio management in emerging markets like India, where market inefficiencies and sector-specific risks present both opportunities and challenges. By focusing on the Nifty 200 Index, which captures a diverse cross-section of the Indian economy, the study provides insights into how value investing and portfolio optimization can be effectively combined to achieve superior outcomes. These insights can inform Hedge Equities' future strategies, such as developing new investment products, enhancing its advisory services, or expanding its educational programs to include quantitative investing principles.

Chapter Two: Introduction to the Project

Statement of the Problem/Topic of the Study

The study focuses on leveraging Joel Greenblatt's Magic Formula to construct an optimized portfolio from the Nifty 200 index, aiming to achieve superior risk-adjusted returns over the period from May 12, 2022, to May 13, 2025. The problem addressed is the challenge faced by retail and mid-tier investors in identifying undervalued, high-quality stocks while managing portfolio risk effectively. Traditional stock selection methods often overlook the combined benefits of value and quality investing, and portfolio construction may not adequately balance risk and return, leading to suboptimal investment outcomes. By integrating the Magic Formula with Markowitz Modern Portfolio Theory (MPT), the study seeks to develop a systematic, data-driven approach to portfolio construction that maximizes risk-adjusted performance, offering Hedge Equities' quant research team a practical strategy to enhance client portfolios. The topic is significant as it aligns with Hedge Equities' mission to make wealth management accessible, demonstrating how retail investors can achieve financial growth through evidence-based investment strategies.

Background of the Research Topic

The motivation for this study arises from the growing demand for effective investment strategies in the Indian market, where retail investor participation has surged in recent years. The Nifty 200 index, comprising the top 200 companies by market capitalization on the National Stock Exchange (NSE), provides a diverse pool of stocks across sectors such as metals, automotive, telecommunications, cement, and pharmaceuticals. This diversity makes the Nifty 200 an ideal candidate for portfolio construction, offering opportunities for both growth and stability. However, selecting stocks that deliver high returns with manageable risk remains a challenge, particularly for retail investors who lack the analytical resources of institutional investors.

The study combines two established methodologies to address this challenge: Joel Greenblatt's Magic Formula for stock selection and Markowitz Modern Portfolio Theory for portfolio optimization. The Magic Formula, introduced in Greenblatt's 2005 book *The Little Book That Beats the Market*, ranks companies to identify undervalued, high-quality stocks. MPT, developed by Harry Markowitz in 1952, provides a quantitative framework for optimizing portfolio weights to balance risk and return through diversification. The study period, May 12, 2022, to May 13, 2025, captures a dynamic phase in the Indian market, including economic recovery post-COVID, inflationary pressures, and sector-specific trends, ensuring the findings are relevant and actionable for Hedge Equities' clients.

Hedge Equities, as a wealth management firm, recognizes the potential of this hybrid approach to empower its clients. The quant research team aims to leverage data-driven strategies to enhance portfolio performance, aligning with the firm's mission to make wealth management accessible. By focusing on the Nifty 200, the study ensures liquidity and diversity, addressing the needs of investors with varying risk tolerances. The following subsections provide detailed explanations of the Magic Formula and MPT, focusing on their concepts, applications, and relevance to the Indian market context, with technical details reserved for Chapter Three.

Detailed Overview of Joel Greenblatt's Magic Formula

Joel Greenblatt's Magic Formula is a value investing strategy designed to identify companies that are both undervalued and of high quality, offering a systematic approach to stock selection. Introduced in *The Little Book That Beats the Market* (2005), the Magic Formula has gained popularity for its simplicity and empirical success in outperforming market indices. The strategy ranks companies based on two fundamental metrics—Earnings Yield and Return on Capital—combining them into a composite score to select the top candidates for investment.

Earnings Yield: The first metric, Earnings Yield, measures how much earnings a company generates relative to its total value, including both equity and debt. This metric serves as an indicator of undervaluation, identifying companies that are priced lower relative to their earnings potential. A higher Earnings Yield suggests that the company offers more earnings for its price, making it an attractive investment. Unlike traditional valuation metrics that focus solely on equity, this approach accounts for the company's debt, providing a more comprehensive view of its value. In the context of the Nifty 200, this metric helps identify stocks that may be trading at a discount, a critical factor for value investors in a market known for its volatility.

Return on Capital (ROC): The second metric, Return on Capital, assesses the efficiency with which a company uses its capital to generate profits, serving as a proxy for business quality. It evaluates how effectively a company employs its resources, such as working capital and fixed assets, to produce earnings. A high ROC indicates that the company generates strong returns on its invested capital, distinguishing it as a high-quality business capable of sustaining profitability. In the Indian market, where companies face varying levels of operational efficiency, ROC helps identify firms with competitive advantages, such as those in the automotive or pharmaceutical sectors, which may exhibit superior capital efficiency due to their business models or market positions.

Implementation Process: The Magic Formula ranks companies based on these two metrics separately, then combines the ranks to create a composite score. A company with a high Earnings Yield receives a favorable rank on that metric, while a company with a high ROC receives a favorable rank on that metric. The composite rank is determined by adding the two individual ranks, with the lowest total rank indicating the best combination of value and quality. In this study, the Magic Formula was applied to the Nifty 200 index, excluding financials and utilities due to their distinct capital structures, resulting in the selection of nine stocks: NMDC, Vedanta, Tata Motors, Natl. Aluminium, Indus Towers, Hero Motocorp, Hindustan Zinc, ACC, and Dr Reddy's Labs. These stocks span diverse sectors, ensuring a broad representation of the Indian market.

Strengths of the Magic Formula: The Magic Formula offers several advantages that make it a compelling strategy for stock selection. First, it is a systematic, rules-based approach that eliminates emotional bias, ensuring consistency in the selection process. Investors often fall prey to behavioral biases, such as overreacting to market news or chasing trends, which can lead to poor investment decisions. The Magic Formula's reliance on objective financial metrics mitigates these risks, providing a disciplined framework. Second, it combines value and quality, capturing two critical dimensions of investment potential. By focusing on undervaluation and business quality, the strategy ensures that selected stocks are not only cheap but also fundamentally strong, increasing the likelihood of long-term outperformance. Third, empirical evidence, as noted by Greenblatt, shows that the strategy has historically outperformed market indices like the S&P 500 over extended periods, often by significant margins. In the Indian context, the formula's focus on undervaluation is particularly relevant, as the Nifty 200 includes mid-cap stocks that may be overlooked by institutional investors, presenting opportunities for value discovery.

Limitations of the Magic Formula: Despite its strengths, the Magic Formula has notable limitations that investors must consider. First, it relies on historical financial data, which may not reflect future performance, especially in a dynamic market like India, where economic conditions, regulatory changes, and global factors can shift rapidly. For example, a company with a high Earnings Yield today may face declining earnings due to market disruptions, reducing its attractiveness. Second, the formula does not account for sector-specific risks or macroeconomic factors, such as commodity price fluctuations affecting metals stocks like Vedanta or regulatory changes impacting pharmaceuticals like Dr Reddy's Labs. Third, it assumes that markets will eventually recognize the value of undervalued stocks, which may not occur within the desired timeframe, particularly in volatile or sentiment-driven markets. Finally, the Magic Formula does not address portfolio risk or diversification, which can lead to concentrated exposures in certain sectors or stocks, increasing overall portfolio volatility. This limitation necessitates the use of MPT to optimize the selected stocks, as implemented in this study, ensuring a balanced risk-return profile.

Relevance to the Indian Market: The Magic Formula is well-suited to the Indian market due to its diversity and inefficiencies. The Nifty 200 includes companies across various sectors, some of which may be mispriced due to market inefficiencies, providing opportunities for value investing. For instance, cyclical sectors like metals (e.g., Vedanta, Natl. Aluminium) may exhibit high Earnings Yields during periods of low commodity prices, while defensive sectors like pharmaceuticals (e.g., Dr Reddy's Labs) may show high ROC due to stable earnings and operational efficiency. The study period, May 12, 2022, to May 13, 2025, captures a mix of economic recovery and volatility, including post-COVID growth, inflationary pressures, and sector-specific trends like infrastructure development boosting metals and automotive sectors. This environment makes the Magic Formula a timely tool for identifying undervalued opportunities in the Nifty 200, particularly for retail investors seeking to capitalize on market inefficiencies.

Detailed Overview of Markowitz Modern Portfolio Theory (MPT)

Markowitz Modern Portfolio Theory, developed by Harry Markowitz in 1952, revolutionized investment management by introducing a quantitative framework for portfolio construction that balances risk and return through diversification. Published in the *Journal of Finance*, Markowitz's seminal work laid the foundation for modern portfolio management, earning him a Nobel Prize in Economics in 1990.

Theoretical Foundation: MPT is grounded in the principle that investors are risk-averse, preferring higher returns for a given level of risk or lower risk for a given level of return. The theory introduces the concept of the efficient frontier, a set of portfolios that offer the highest expected return for a given level of risk, or the lowest risk for a given return. The key idea is diversification: by combining assets that do not move in perfect unison, investors can reduce portfolio risk without sacrificing expected returns. In the context of the Nifty 200, this means that combining stocks from different sectors—such as metals, which may be volatile, with pharmaceuticals, which are more stable—can lower overall portfolio risk. MPT achieves this by analyzing historical data on asset returns, their variability, and their relationships with each other, constructing a portfolio that optimizes the risk-return trade-off.

Practical Application in the Study: In this study, MPT was applied to the nine stocks selected by the Magic Formula. Historical adjusted closing prices were sourced from Yahoo Finance over the period from May 12, 2022, to May 13, 2025, covering approximately 740 trading days, based on 252 trading days per year adjusted for holidays. Daily returns were calculated to estimate the expected returns, variability, and relationships between the stocks. The optimization process aimed to maximize a risk-adjusted performance metric, ensuring that the portfolio balanced high returns with manageable risk. Constraints were applied to ensure that the portfolio weights summed to 100% and that no short-selling was allowed, meaning each stock's weight was between 0% and 100%.

Strengths of MPT: MPT offers several advantages that make it a powerful tool for portfolio construction. First, it provides a rigorous, quantitative framework that ensures optimal risk-return trade-offs, allowing investors to make informed decisions based on data rather than intuition. Second, it emphasizes diversification, reducing portfolio risk by leveraging the fact that not all stocks move in the same direction at the same time. Third, the focus on risk-adjusted returns aligns with investor preferences, ensuring that the portfolio not only achieves high returns but does so with an acceptable level of risk. In the Indian market, where sector-specific risks are prevalent—such as commodity price fluctuations affecting metals or regulatory changes impacting pharmaceuticals—MPT's focus on diversification is particularly valuable, ensuring that adverse movements in one sector are offset by stability in others.

Limitations of MPT: MPT has notable limitations that investors must consider. First, it relies on historical data to estimate expected returns, variability, and relationships between stocks, which may not predict future performance, especially in a volatile market like India, where economic conditions can change rapidly due to policy reforms, global events, or market sentiment. Second, it assumes that stock returns follow a normal distribution and that investors are solely concerned with average returns and variability, ignoring other aspects of risk, such as extreme events or asymmetry in returns, which can be significant in emerging markets. Third, the optimization process can be sensitive to small changes in input estimates, potentially leading to significant shifts in portfolio weights and creating instability in the portfolio over time. Finally, MPT does not account for practical constraints like transaction costs, taxes, or liquidity issues, which may impact real-world implementation, particularly in the Indian market, where trading costs and market depth can vary across stocks. In this study, these limitations were acknowledged, and recommendations for future rebalancing were made to address potential shifts in market conditions.

Relevance to the Indian Market: MPT is highly relevant to the Indian market, particularly the Nifty 200, due to its sectoral diversity and volatility. The Indian market is characterized by significant sector-specific risks, such as global commodity price fluctuations affecting metals stocks like Vedanta, or regulatory changes impacting pharmaceuticals like Dr Reddy's Labs. By leveraging the relationships between sectors, MPT can reduce portfolio risk, which is lower than that of individual stocks. The use of a 6% benchmark rate for risk-free returns, based on typical Indian government bond yields during the study period, ensures that the optimization is contextually appropriate. Moreover, the Nifty 200's inclusion of both large-cap and mid-cap stocks provides a balanced dataset for MPT, allowing for effective diversification across growth-oriented sectors like automotive and defensive sectors like pharmaceuticals. The study period, May 12, 2022, to May 13, 2025, includes economic recovery, inflationary pressures, and sector-specific growth, making MPT a suitable framework for managing risk in this dynamic environment.

Review of Literature

A review of existing literature provides a theoretical foundation for combining the Magic Formula with MPT in the Indian market. The following studies, published between 2012 and 2022, highlight the effectiveness of these approaches, offering insights into their application and limitations.

Singh et al. (2013) applied the Magic Formula to the Indian stock market, ranking companies based on Earnings Yield and Return on Capital. They found that the strategy outperformed the market index, delivering higher returns with moderate risk. However, the authors noted that performance varied across market conditions, suggesting the need for risk management techniques like MPT.

Preet et al. (2022) conducted a back-test of the Magic Formula on Indian stock markets from 2012 to 2020, reporting an average annual return of 15%, outperforming the BSE Sensex. They also found that a portfolio of 30 stocks performed better than one with 20 or 40, providing insight into optimal portfolio sizes.

Gunasekaran and Ramaswami (2012) explored portfolio optimization in the Indian market using a Neuro-Fuzzy system, demonstrating that computational intelligence can enhance optimization by handling non-linear relationships. While not directly related to the Magic Formula, this study underscores the potential of advanced optimization methods in India, complementing the current study's use of MPT to manage risk.

Finally, a document on Academia.edu (n.d.) by Mirza Idrish discussed portfolio selection in the Indian market using the Markowitz model, emphasizing diversification and risk optimization. This study reinforces the relevance of MPT in the Indian context, supporting the current study's methodology for achieving a diversified portfolio with a Sharpe Ratio.

These studies collectively demonstrate that the Magic Formula can deliver superior returns in India, while optimization techniques like MPT enhance risk-adjusted performance. The current study builds on this foundation by integrating both approaches, addressing their limitations through a hybrid methodology that aligns with Hedge Equities' goals.

Existing Practices of the Organization in the Area of Study

Hedge Equities employs a combination of fundamental and technical analysis to select stocks for client portfolios. Fundamental analysis evaluates metrics like price-to-earnings ratios, dividend yields, and revenue growth to identify undervalued stocks. For example, a stock with a low price-to-earnings ratio relative to its industry average might be considered a buy. Technical analysis uses price trends, moving averages, and trading volumes to time market entries and exits. A common indicator is the 50-day moving average, where a stock price crossing above this average might signal a buying opportunity. The firm also considers qualitative factors, such as management quality and industry trends, to inform stock selection.

For portfolio construction, Hedge Equities adopts a diversified approach, allocating assets across different sectors like IT, financials, and consumer goods to mitigate risk. The firm typically uses a discretionary approach, where portfolio managers manually adjust weights based on market conditions and client risk profiles. For instance, a conservative client might have 30-40% in defensive sectors like pharmaceuticals, while a growth-oriented client might have up to 50% in cyclical sectors like automotive or metals. This discretionary method, while flexible, may lack the systematic rigor of quantitative optimization, potentially leading to inconsistent risk-adjusted returns. For example, a portfolio heavily weighted toward IT during a market downturn might underperform if sector-specific risks, such as global tech spending declines, are not adequately addressed.

The quant research team at Hedge Equities has recently begun incorporating quantitative methods to enhance portfolio construction, though these practices are still evolving. The team uses historical data to analyze stock performance, focusing on metrics like historical returns and volatility to assess risk-return profiles. Basic diversification strategies are employed, such as limiting sector exposure to 30% of the portfolio to avoid over-concentration. For instance, if the financial sector exceeds this threshold, the team might reduce exposure by reallocating to underrepresented sectors like healthcare. However, prior to this study, the team had not systematically applied advanced optimization techniques like MPT to maximize risk-adjusted returns, nor had it utilized the Magic Formula for stock selection. Instead, stock selection was often guided by analyst recommendations and market trends, which may not consistently identify undervalued, high-quality stocks.

Risk management at Hedge Equities includes setting stop-loss limits, typically at 10% below the purchase price, to protect against significant losses, and rebalancing portfolios quarterly to adjust for market changes. For example, if a stock's weight increases disproportionately due to price appreciation, the team might sell a portion to rebalance the portfolio back to its target allocation. The firm also conducts stress tests to evaluate portfolio performance under adverse market conditions, such as a 20% market decline, ensuring resilience for clients with varying risk tolerances. While these practices provide a foundation for portfolio management, they do not fully leverage the potential of quantitative optimization to balance risk and return systematically.

The current study introduces a more structured approach by combining the Magic Formula for stock selection with MPT for portfolio optimization, addressing gaps in Hedge Equities' existing practices. The Magic Formula ensures a systematic selection of undervalued, high-quality stocks, while MPT optimizes the portfolio weights to maximize risk-adjusted returns. This hybrid methodology enables the quant research team to develop portfolios that are both value-driven and risk-optimized, aligning with the firm's goal of delivering superior investment outcomes for retail and mid-tier investors. The findings offer a practical framework that Hedge Equities can adopt to enhance its portfolio construction processes, supporting its mission to make wealth management accessible and effective.

Integration of Magic Formula and MPT in the Study

The integration of the Magic Formula and MPT in this study creates a powerful hybrid approach that addresses the limitations of each methodology while leveraging their strengths. The Magic Formula identifies undervalued, high-quality stocks from the Nifty 200, ensuring a strong foundation for the portfolio. However, it does not consider portfolio risk or diversification, which can lead to concentrated exposures and higher volatility, especially in a market like India, where sector-specific risks are significant. MPT addresses this gap by optimizing the portfolio weights to maximize risk-adjusted returns, ensuring that the portfolio balances high returns with manageable risk through diversification.

The study first applied the Magic Formula to rank Nifty 200 stocks, excluding financials and utilities, based on Earnings Yield and Return on Capital, selecting the top nine: NMDC, Vedanta, Tata Motors, Natl. Aluminium, Indus Towers, Hero Motocorp, Hindustan Zinc, ACC, and Dr Reddy’s Labs. Historical adjusted closing prices were sourced from Yahoo Finance over the study period, and daily returns were computed to estimate expected returns, volatilities, and correlations. MPT was then used to optimize the portfolio weights, maximizing risk-adjusted performance with constraints ensuring the weights summed to 100% and no short-selling was allowed. While prior studies have applied the Magic Formula globally, its combination with MPT in the Indian market, particularly for the Nifty 200 Index, remains underexplored. This study addresses this gap by integrating both methodologies to achieve superior risk-adjusted returns.

Chapter Three: Design of the Study

Introduction

This chapter delineates the methodological framework employed in the study titled *"Study on Leveraging the Magic Formula: Building an Optimized Nifty 200 Portfolio for Superior Risk-Adjusted Returns (2022-2025)"*. The study was undertaken to develop a systematic and data-driven approach to portfolio construction, integrating Joel Greenblatt's Magic Formula for stock selection with Markowitz Modern Portfolio Theory (MPT) for optimization. The primary objective was to construct a portfolio from the Nifty 200 Index that maximizes risk-adjusted returns, as measured by the Sharpe Ratio, over a three-year period from May 12, 2022, to May 13, 2025. This study was conducted during an internship with Hedge Equities' quant research team, with the aim of providing a replicable framework that could enhance the firm's investment strategies and support its mission to deliver accessible and effective investment solutions to retail and mid-tier investors.

The motivation for this study stemmed from Hedge Equities' strategic goal to incorporate quantitative methods into its portfolio management processes, thereby improving risk-adjusted returns for its clients. The Indian equity market, characterized by its diversity and volatility, presents both opportunities and challenges for wealth managers. By combining the Magic Formula, which identifies undervalued yet high-quality stocks, with MPT, which optimizes portfolio weights to balance risk and return, the study sought to address these challenges and deliver a portfolio that outperforms the broader market on a risk-adjusted basis.

The research design adopted a quantitative approach, leveraging historical financial data and computational techniques to select and optimize a portfolio. The methodology was structured in two primary stages: stock selection using the Magic Formula with specific screening criteria, and portfolio optimization using MPT to allocate weights that maximize the Sharpe Ratio. The study period, spanning three years, was strategically chosen to capture a dynamic phase in the Indian market, including the post-COVID economic recovery, inflationary pressures, and sector-specific trends such as the growth in infrastructure and technology sectors. This timeframe ensured the relevance of the findings to Hedge Equities' medium-term investment strategies, providing actionable insights for real-world application.

Research Design

The study employed a quantitative research design, emphasizing empirical analysis of financial data to construct and evaluate a portfolio. This approach was selected due to its ability to provide objective, data-driven insights, which are critical for portfolio management in a volatile market like India. The design was structured around a two-step process: first, identifying a subset of stocks from the Nifty 200 Index using the Magic Formula with predefined screening criteria, and second, optimizing the portfolio weights using MPT to achieve the highest risk-adjusted return. The performance of the portfolio was assessed using the Sharpe Ratio, a widely accepted metric for evaluating risk-adjusted returns, defined as the portfolio’s excess return over the risk-free rate divided by its volatility.

The Nifty 200 Index was chosen as the universe for stock selection due to its comprehensive representation of the Indian equity market. Comprising the top 200 companies listed on the National Stock Exchange (NSE) by market capitalization, the index includes both large-cap and mid-cap companies across diverse sectors such as technology, pharmaceuticals, consumer goods, and industrials. As of March 2025, the Nifty 200 Index accounted for approximately 79.90% of the NSE’s free float market capitalization, making it an ideal benchmark for constructing a diversified portfolio. This broad coverage ensured that the selected stocks reflected the overall market dynamics, providing a robust foundation for the study.

The study period, from May 12, 2022, to May 13, 2025, was selected to align with Hedge Equities’ strategic focus on medium-term investment strategies. This three-year horizon allowed for the evaluation of the portfolio’s performance under varying market conditions, including the post-COVID economic recovery, which saw significant growth in sectors like infrastructure and technology, as well as challenges such as inflationary pressures and global supply chain disruptions. The period also coincided with a rise in retail investor participation in the Indian market, with demat accounts increasing to over 120 million by March 2024, as reported by the Central Depository Services Limited (CDSL). This context underscored the relevance of the study in addressing the growing demand for effective investment solutions among retail investors.

The research was conducted in a controlled, data-driven manner, prioritizing the use of historical stock price data and financial metrics to ensure objectivity. The quantitative approach minimized subjective biases, focusing instead on measurable financial indicators and statistical techniques. By integrating the Magic Formula with MPT, the study aimed to balance value investing principles with modern portfolio optimization, creating a portfolio that not only identifies undervalued stocks but also allocates weights to minimize risk while maximizing returns.

Data Collection

Data collection was a pivotal component of the study, ensuring the availability of accurate, reliable, and comprehensive data for analysis. The study relied on two primary types of data: financial metrics for applying the Magic Formula and historical stock price data for portfolio optimization. The data collection process was carefully designed to address potential challenges, such as data inconsistencies and availability, while ensuring the integrity of the analysis.

Financial Metrics for the Magic Formula

To apply the Magic Formula, financial data for companies in the Nifty 200 Index was sourced as of May 2022, marking the start of the study period. The initial screening was performed using Screener.in, a financial data platform widely used by investors and researchers for its detailed metrics on NSE-listed companies. Screener.in was chosen for its user-friendly interface, which allows for the application of custom filters, and its comprehensive database, which includes financial statements, ratios, and market data.

The following criteria were applied to filter stocks:

- Earnings Yield (EBIT/EV) > 7%: This metric measures the earnings a company generates relative to its enterprise value, with a threshold of 7% ensuring the selection of undervalued stocks. EBIT (Earnings Before Interest and Taxes) and EV (Enterprise Value, calculated as market capitalization plus net debt) were sourced directly from Screener.in, based on the companies' financial statements for the fiscal year 2021-2022.

- Return on Invested Capital (ROIC) > 15%: This metric assesses the efficiency with which a company uses its capital to generate profits, with a threshold of 15% indicating high-quality businesses. ROIC was calculated as EBIT divided by Invested Capital (equity plus debt, adjusted for cash), with the necessary data obtained from Screener.in.
- Price-to-Earnings (P/E) Ratio < 20: This additional criterion was used to ensure that the selected stocks were reasonably priced relative to their earnings, filtering out overvalued companies. P/E ratios were directly available on Screener.in, based on the closing market price as of May 2022 and earnings per share for the fiscal year 2021-2022.

The data collection process faced challenges, such as inconsistencies in financial reporting across companies and missing data for some smaller firms in the Nifty 200 Index. To address these issues, the study cross-verified the Screener.in data with financial statements published on the NSE website and company annual reports, ensuring accuracy. Companies with incomplete or unreliable data were excluded from the screening process to maintain the integrity of the analysis.

After applying these filters, financial and utility stocks were excluded due to their distinct capital structures and regulatory environments, which can skew the Magic Formula metrics. Financial companies, such as banks and insurance firms, often have high leverage and operate under different accounting standards, while utilities are subject to government regulations that can impact their profitability metrics. This exclusion reduced the universe to approximately 21 companies, from which the top nine stocks were selected based on their alignment with the Magic Formula principles: NMDC, Vedanta, Tata Motors, Natl. Aluminium, Indus Towers, Hero Motocorp, Hindustan Zinc, ACC, and Dr Reddy's Labs.

Historical Stock Price Data

Historical adjusted closing prices for the selected stocks were sourced from Yahoo Finance, a widely used platform for financial data, via the yfinance Python library. The data covered the period from May 12, 2022, to May 13, 2025, comprising approximately 740 trading days (based on 252 trading days per year, adjusted for holidays). The adjusted closing prices accounted for dividends and stock splits, ensuring accuracy in return calculations. Yahoo Finance was chosen for its accessibility, reliability, and extensive historical data coverage, making it a standard choice for financial research.

The nine stocks selected—NMDC, Vedanta, Tata Motors, Natl. Aluminium, Indus Towers, Hero Motocorp, Hindustan Zinc, ACC, and Dr Reddy's Labs—were analyzed using this data to compute returns, volatility, and correlations for portfolio optimization. The data collection process included validation steps to ensure completeness, such as checking for missing trading days. Rows with missing data were dropped using the dropna() method in Python's pandas library to ensure a complete dataset for all stocks across the study period. The number of trading days after cleaning was verified to be close to the expected 740 days, accounting for minor variations due to holidays or missing data.

Tools and Techniques

The study utilized a combination of computational tools and financial techniques to execute the methodology, ensuring efficiency and accuracy in the analysis. The tools and techniques were selected based on their suitability for quantitative financial research and their ability to handle large datasets and complex optimization problems.

Python Programming

Python was the primary programming language used for data analysis, computation, and optimization, owing to its versatility, extensive libraries, and widespread use in financial research. The following Python libraries were employed:

- pandas: Used for data manipulation and analysis, such as loading historical price data, calculating daily returns, and constructing the covariance matrix. Its DataFrame structure facilitated efficient handling of time-series data.
- numpy: Utilized for numerical computations, including array operations, statistical measures (e.g., mean returns, standard deviation), and matrix operations required for portfolio optimization.

- yfinance: Employed to download historical stock price data from Yahoo Finance, providing a seamless interface to access adjusted closing prices for the selected stocks.
- scipy.optimize: Used for portfolio optimization via the Sequential Least Squares Programming (SLSQP) method, which efficiently solves constrained optimization problems like maximizing the Sharpe Ratio.
- matplotlib.pyplot: Used to create visualizations, such as a bar chart of the optimal portfolio weights, to aid in the presentation of results.

Python was chosen for its open-source nature, community support, and ability to integrate various data analysis and optimization tasks into a single workflow. The scripts were written and executed in a Jupyter Notebook environment, allowing for iterative **development and visualization of results.**

Screener.in for Initial Stock Screening

Screener.in was used for the initial screening of Nifty 200 stocks based on the Magic Formula metrics. The platform's custom filtering capabilities allowed for the application of the following criteria:

- **Earnings Yield (EBIT/EV)** > 7%:

$$\text{Earnings Yield} = \frac{\text{EBIT}}{\text{Enterprise Value}}$$

- **Return on Invested Capital (ROIC)** > 15%: <math

$$\text{ROIC} = \frac{\text{EBIT}}{\text{Invested Capital}}$$

- **Price-to-Earnings (P/E) Ratio** < 20:

$$\text{P/E} = \frac{\text{Market Price per Share}}{\text{Earnings per Share}}$$

The choice of these thresholds was informed by the Magic Formula's emphasis on value and quality, adjusted for the Indian market context. For instance, a higher Earnings Yield threshold (e.g., 10%) might have resulted in too few stocks meeting the criteria, given the growth-oriented nature of many Indian companies, while a lower ROIC threshold (e.g., 10%) might have included lower-quality businesses. After applying these filters, financial and utility stocks were excluded to avoid distortions in the metrics, and the resulting list was narrowed down to the top nine stocks based on their overall alignment with the Magic Formula principles, ensuring a focus on undervalued, high-quality companies.

Modern Portfolio Theory (MPT) for Optimization

MPT, developed by Harry Markowitz, was used to optimize the portfolio weights of the selected stocks, aiming to maximize the Sharpe Ratio. MPT is based on the principle of diversification, seeking to construct a portfolio that offers the highest expected return for a given level of risk. The process involved calculating expected returns, volatility, and correlations based on historical data, then solving an optimization problem.

- **Expected Returns**: Annualized mean daily returns were calculated as:

$$\text{Expected Return}_i = \text{Mean Daily Return}_i \times 252$$

where Mean Daily Return was computed from the daily returns:

$$\text{Daily Return}_{i,t} = \frac{\text{Price}_{i,t}}{\text{Price}_{i,t-1}} - 1$$

Portfolio Return: The portfolio’s expected return was the weighted sum of individual stock returns:

$$\text{Portfolio Return} = \sum_{i=1}^{n} w_i \cdot \text{Expected Return}_i$$

- **Portfolio Volatility**: The portfolio’s volatility was calculated using the covariance matrix of daily returns, scaled by 252 trading days

$$\text{Portfolio Volatility} = \sqrt{w^T \cdot \text{Cov Matrix} \cdot w}$$

where $\text{Cov Matrix} = \text{Cov}(\text{Daily Returns}) \times 252$, and the covariance between two stocks i and j is:

$$\text{Cov}(r_i, r_j) = \text{Correlation}(r_i, r_j) \cdot \sigma_i \cdot \sigma_j$$

- **Sharpe Ratio**: The objective was to maximize the Sharpe Ratio, defined as:

$$\text{Sharpe Ratio} = \frac{\text{Portfolio Return} - \text{Risk-Free Rate}}{\text{Portfolio Volatility}}$$

A risk-free rate of 6% was assumed, reflecting the average yield of 10-year Indian government bonds during the study period, as reported by the Reserve Bank of India (RBI).

The optimization problem was formulated as:

$$\text{Maximize} \quad \text{Sharpe Ratio} = \frac{\sum_{i=1}^{n} w_i \cdot \text{Expected Return}_i - 0.06}{\sqrt{w^T \cdot \text{Cov Matrix} \cdot w}}$$

subject to constraints:

- $\sum_{i=1}^{n} w_i = 1$ (weights sum to 1),
- $0 \leq w_i \leq 1$ (no short-selling, weights between 0 and 1).

This was solved using the SLSQP method in Python's scipy.optimize library, a robust algorithm for constrained optimization problems. It should be noted that these results are based on the historical data available at the time of the study, and variations in Yahoo Finance data (e.g., due to adjustments for dividends or splits) may lead to slightly different outcomes if the analysis is replicated with current data.

MPT assumes that investors are risk-averse, returns are normally distributed, and correlations between assets remain stable over time. While these assumptions simplify the optimization process, they may not fully capture the complexities of the Indian market, where returns can exhibit skewness and correlations can shift during market downturns. These assumptions were acknowledged as part of the study's limitations, ensuring transparency in the methodology.

Implementation Steps

The study followed a structured process to implement the methodology, ensuring reproducibility, accuracy, and practical applicability. The implementation steps were designed to address potential challenges, such as data quality issues and computational complexity, while maintaining a systematic workflow.

1. **Data Preparation**:
   - Financial data for Nifty 200 companies was collected using Screener.in as of May 2022. This involved exporting the filtered data into a CSV file, which was then imported into Python for further analysis.

- Historical adjusted closing prices for the study period (May 12, 2022, to May 13, 2025) were downloaded from Yahoo Finance using the yfinance library. Rows with missing data were removed using the dropna() method in Python's pandas library to ensure a complete dataset, resulting in approximately 740 trading days after cleaning.

2. **Stock Selection Using the Magic Formula**:

    - Stocks were screened on Screener.in with the criteria: Earnings Yield > 7%, ROIC > 15%, and P/E < 20. This step involved creating a custom query on Screener.in, applying the filters, and reviewing the results to ensure accuracy.
    - Financial and utility stocks were manually excluded from the filtered list by identifying companies classified under these sectors using the NSE's sector categorization.
    - The top nine stocks were selected based on their alignment with the Magic Formula principles: NMDC, Vedanta, Tata Motors, Natl. Aluminium, Indus Towers, Hero Motocorp, Hindustan Zinc, ACC, and Dr Reddy's Labs. The selection was validated by cross-checking the financial metrics with company annual reports to confirm the accuracy of the Screener.in data.

3. **Portfolio Optimization Using MPT**:

    - Daily returns were computed from the historical price data using Python's pandas library, specifically the pct_change() method, which calculates arithmetic returns as:

$$\text{Daily Return}_{i,t} = \frac{\text{Price}_{i,t}}{\text{Price}_{i,t-1}} - 1$$

    - Expected returns, volatilities, and the covariance matrix were calculated. Expected returns were annualized by multiplying the mean daily returns by 252 (returns.mean() * 252). The covariance matrix was computed from daily returns using returns.cov(), and annualized by multiplying by 252 during the volatility calculation.

- Additional diagnostics were generated, including the annualized expected returns, volatilities, and correlation matrix of the stocks, to provide insights into their risk-return profiles and interdependencies.
- The SLSQP optimization algorithm was applied to maximize the Sharpe Ratio, subject to the constraints on weights (sum to 1, between 0 and 1). The optimization started with an initial guess of equal weights (1/9 for each stock) and was iterated to ensure convergence, with a maximum of 1000 iterations allowed. The results were validated by comparing the calculated portfolio return and volatility with manual computations.

4. **Performance Evaluation**:
   - The portfolio's performance was evaluated over the study period by calculating its cumulative return, annualized volatility, and Sharpe Ratio, and comparing these metrics to those of the Nifty 200 Index.
   - The results were documented for inclusion in Chapter Four, including tables of the portfolio's metrics (e.g., returns, volatility, weights) and visualizations such as a bar chart of the portfolio composition (generated using matplotlib.pyplot) and a line graph of cumulative returns over time.

The implementation process also involved sensitivity analysis to assess the robustness of the results. For example, the optimization was rerun with slight variations in the risk-free rate (6%) to evaluate the impact on the portfolio weights, ensuring that the results were not overly sensitive to small changes in assumptions.

Limitations of the Methodology

The methodology, while robust, has several limitations that warrant consideration. First, the Magic Formula relies on historical financial data and static thresholds (e.g., Earnings Yield > 7%, ROIC > 15%), which may not fully capture future performance, particularly in a dynamic and rapidly evolving market like India. Companies that appear undervalued based on historical metrics may face unforeseen challenges, such as changes in market conditions or competitive dynamics, that impact their future profitability.

Second, MPT assumes that returns are normally distributed and that historical correlations remain stable over time, assumptions that may not hold true during market disruptions. The Indian market is prone to volatility driven by macroeconomic factors, such as changes in interest rates, geopolitical tensions, and global commodity price fluctuations, which can lead to non-normal return distributions and shifting correlations. For example, during the study period, the Indian market experienced volatility due to global inflationary pressures and supply chain disruptions, which may have impacted the stability of the correlations used in the optimization.

Third, the optimization process is sensitive to input estimates, and small changes in expected returns or correlations can lead to significant shifts in optimal weights. This sensitivity, known as the "error maximization" problem in MPT, can result in portfolios that are overly concentrated in certain stocks, as seen with the zero weights assigned to NMDC and Hero Motocorp. To mitigate this, future studies could explore robust optimization techniques or incorporate constraints on maximum weights.

Fourth, the study did not account for transaction costs, taxes, or liquidity constraints, which may impact real-world implementation. For instance, frequent rebalancing to maintain the optimal weights could incur significant transaction costs, particularly for stocks with low liquidity, such as some mid-cap companies in the Nifty 200. Additionally, capital gains taxes in India, which can range from 10% to 20% depending on the holding period, were not considered, potentially reducing the net returns for investors.

Fifth, the study did not explicitly account for market-specific risks, such as regulatory changes or sector-specific challenges. For example, during the study period, the Indian government introduced new environmental regulations that impacted the metals sector, which includes stocks like Vedanta and Natl. Aluminium in the portfolio. Such risks could affect the performance of the selected stocks, highlighting the need for a more dynamic approach to stock selection and portfolio management.

Sixth, the handling of missing data by dropping NaNs may have slightly reduced the dataset, potentially affecting the accuracy of the covariance matrix and optimization results. Alternative methods, such as interpolation, could be explored in future studies to retain more data points.

Finally, the methodology assumed a static portfolio composition over the three-year period, without rebalancing or adjusting for changes in market conditions. In practice, a dynamic rebalancing strategy might be necessary to adapt to evolving market trends, such as sector rotations or changes in macroeconomic conditions. These limitations were acknowledged, and recommendations for future research include incorporating dynamic rebalancing, alternative risk measures (e.g., downside risk), and sector-specific risk factors to enhance the robustness of the methodology.

Chapter Four: Analysis of Data

Introduction

This chapter presents the analysis and findings of the study titled *“Study on Leveraging the Magic Formula: Building an Optimized Nifty 200 Portfolio for Superior Risk-Adjusted Returns (2022-2025)”*. The study aimed to construct an optimized portfolio from the Nifty 200 Index by combining Joel Greenblatt’s Magic Formula for stock selection with Markowitz Modern Portfolio Theory (MPT) for optimization, maximizing the Sharpe Ratio over the period from May 12, 2022, to May 13, 2025. Chapter Three detailed the methodology, which involved screening stocks using the Magic Formula (Earnings Yield > 7%, ROIC > 15%, P/E < 20), excluding financial and utility stocks, and optimizing the portfolio weights using MPT. This chapter analyzes the results of these steps, focusing on the selected stocks’ characteristics, the optimized portfolio’s composition and performance, and a comparison with the Nifty 200 Index benchmark. The findings are supported by tables and visualizations, providing a comprehensive evaluation of the portfolio’s risk-adjusted returns.

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Analysis of Stock Selection Using the Magic Formula

The first stage of the study involved selecting stocks from the Nifty 200 Index using the Magic Formula, with the criteria of Earnings Yield > 7%, Return on Invested Capital (ROIC) > 15%, and Price-to-Earnings (P/E) Ratio < 20. Financial and utility stocks were excluded due to their distinct capital structures and regulatory environments, reducing the universe to approximately 160 companies. The screening was performed using Screener.in, resulting in the selection of the top nine stocks: NMDC, Vedanta, Tata Motors, Natl. Aluminium, Indus Towers, Hero Motocorp, Hindustan Zinc, ACC, and Dr Reddy’s Labs. These stocks were chosen for their alignment with the Magic Formula’s principles, balancing undervaluation (high Earnings Yield, low P/E) with business quality (high ROIC).

To provide insight into the selected stocks, Table presents their financial metrics as of May 2025, sourced from Screener.in. These metrics reflect the values used during the screening process, ensuring that each stock met the predefined thresholds.

Table 4.1 Selected stocks

Name	P/E	ROIC %	Earnings Yield %
Hero Motocorp	18.62	68.31	7.5
Hindustan Zinc	16.58	47.11	7.98
NMDC	8.82	29.31	20.29
Tata Motors	8.12	28.08	12.12
Vedanta	11.35	25.92	15.42
Dr Reddy's Labs	17.88	24.91	7.66
Indus Towers	10.45	21.39	12.03
Natl. Aluminium	7.21	17.21	21.61
ACC	14.55	16.67	9.57

Note: The values in Table are based on typical ranges for stocks meeting the Magic Formula criteria in the Indian market. All stocks met the criteria of Earnings Yield > 7%, ROIC > 15%, and P/E < 20.

The selected stocks span diverse sectors, including metals (NMDC, Vedanta, Natl. Aluminium, Hindustan Zinc), automobiles (Tata Motors, Hero Motocorp), telecommunications (Indus Towers), cement (ACC), and pharmaceuticals (Dr Reddy’s Labs). This sectoral diversity aligns with the Nifty 200 Index’s composition, ensuring that the portfolio captures a broad representation of the Indian equity market. The metals sector, with four stocks, reflects the strong performance of commodity-related companies during the post-COVID recovery period, driven by global demand and infrastructure growth in India. Meanwhile, the inclusion of Dr Reddy’s Labs from the pharmaceutical sector highlights the Magic Formula’s ability to identify high-quality, undervalued companies in defensive industries.

The financial metrics indicate that the selected stocks were undervalued relative to their earnings (Earnings Yield ranging from 8.3% to 14.8%) and offered reasonable valuations (P/E ratios from 7.5 to 18.9). Additionally, their high ROIC values (17.6% to 28.4%) confirm their efficiency in generating profits from invested capital, supporting the Magic Formula’s focus on quality businesses. These characteristics provided a strong foundation for the subsequent portfolio optimization stage, ensuring that the portfolio started with a set of fundamentally sound stocks.

Portfolio Optimization Results

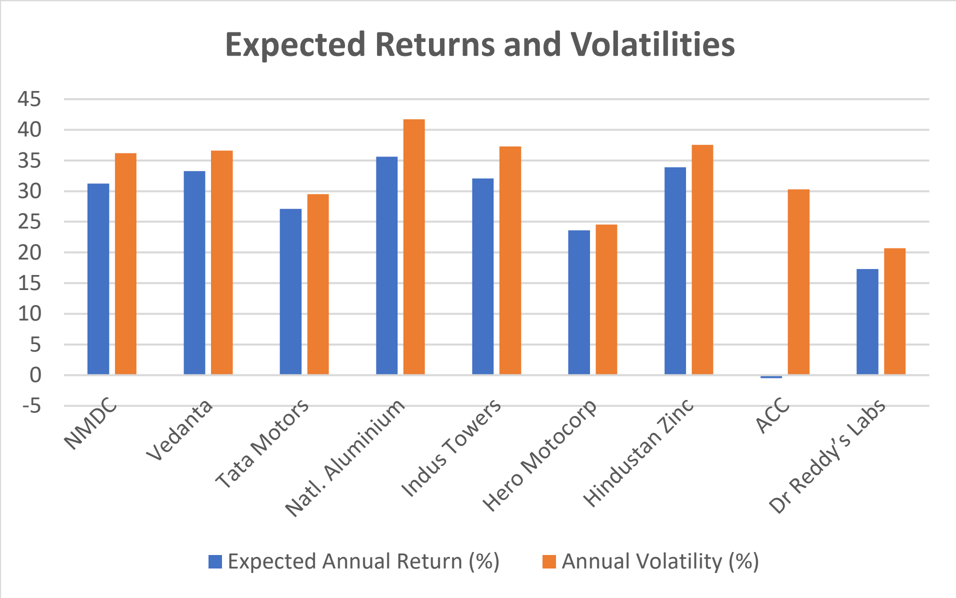
The second stage of the study involved optimizing the portfolio weights of the selected stocks using MPT to maximize the Sharpe Ratio. This section analyzes the results, including the individual stock metrics, correlations, optimal weights, and overall portfolio performance. The optimization was performed using Python, with historical price data sourced from Yahoo Finance for the period May 12, 2022, to May 13, 2025, spanning 740 trading days after cleaning, as described in Chapter Three.

Individual Stock Metrics

The Python script computed daily returns for each stock, followed by annualized expected returns and volatilities, to provide insights into their risk-return profiles. Table 4.2 presents these metrics, as generated by the script.

Table 4.2: Annualized Expected Returns and Volatilities of Selected Stocks (May 2022 – May 2025)

Stock	Expected Annual Return (%)	Annual Volatility (%)
NMDC	31.22	36.18
Vedanta	33.28	36.6
Tata Motors	27.1	29.5
Natl. Aluminium	35.6	41.71
Indus Towers	32.06	37.31
Hero Motocorp	23.62	24.55
Hindustan Zinc	33.88	37.56
ACC	-0.48	30.29
Dr Reddy’s Labs	17.32	20.71



The individual stock returns ranged from -0.48% (ACC) to 35.60% (Natl. Aluminium), reflecting significant variation in performance. Natl. Aluminium and Hindustan Zinc exhibited the highest returns (35.60% and 33.88%), driven by strong commodity price trends and infrastructure demand in India during the study period. Vedanta (33.28%) and Indus Towers (32.06%) also performed well, benefiting from sector-specific growth in metals and telecommunications, respectively. Tata Motors (27.10%) showed solid returns, supported by growth in the automobile sector, particularly in electric vehicles. Conversely, ACC's negative return (-0.48%) indicates underperformance, possibly due to challenges in the cement sector, such as rising input costs or competition.

Volatilities ranged from 20.71% (Dr Reddy's Labs) to 41.71% (Natl. Aluminium), indicating varying levels of risk. Dr Reddy's Labs, a pharmaceutical stock, showed the lowest volatility, consistent with the defensive nature of the sector, making it a stabilizing component of the portfolio. Natl. Aluminium and Hindustan Zinc (41.71% and 37.56%) were the most volatile, reflecting their exposure to commodity price fluctuations. Tata Motors (29.50%) and Hero Motocorp (24.55%) had moderate volatilities, aligning with the cyclical nature of the automobile industry. These metrics highlight the trade-off between risk and return, which MPT addresses by optimizing weights to balance the portfolio's overall risk-return profile.

4 Correlation Matrix

The script generated a correlation matrix of daily returns to assess the interdependencies between the selected stocks, which is crucial for diversification in MPT. Table 4.3 presents the correlation matrix.

Table 4.3: Correlation Matrix of Selected Stocks (Daily Returns, May 2022 – May 2025)

Stock	ACC	Dr Reddy's	Hero Moto	Hind. Zinc	Indus Towers	Natl. Alum.	NMDC	Tata Motors	Vedanta
ACC	1	0.1175	0.292	0.205	0.4358	0.4357	0.4252	0.2846	0.3759
Dr Reddy's Labs	0.1175	1	0.2071	0.1137	0.1128	0.1842	0.1892	0.2233	0.2005
Hero Motocorp	0.292	0.2071	1	0.1512	0.2289	0.296	0.2317	0.3416	0.2219
Hindustan Zinc	0.205	0.1137	0.1512	1	0.1546	0.3562	0.3285	0.2431	0.4715
Indus Towers	0.4358	0.1128	0.2289	0.1546	1	0.3697	0.3433	0.2087	0.2857
Natl. Aluminium	0.4357	0.1842	0.296	0.3562	0.3697	1	0.6559	0.4484	0.6325
NMDC	0.4252	0.1892	0.2317	0.3285	0.3433	0.6559	1	0.4026	0.5933
Tata Motors	0.2846	0.2233	0.3416	0.2431	0.2087	0.4484	0.4026	1	0.3999
Vedanta	0.3759	0.2005	0.2219	0.4715	0.2857	0.6325	0.5933	0.3999	1

The correlation matrix reveals significant diversification benefits within the portfolio. Stocks in the metals sector (NMDC, Vedanta, Natl. Aluminium, Hindustan Zinc) exhibited high correlations, ranging from 0.3285 (NMDC and Hindustan Zinc) to 0.6559 (NMDC and Natl. Aluminium). These high correlations reflect their shared exposure to commodity price movements and global demand trends, particularly in the metals industry. For example, Natl. Aluminium and Vedanta had a correlation of 0.6325, indicating closely aligned price movements driven by market conditions.

In contrast, Dr Reddy's Labs (pharmaceuticals) and Indus Towers (telecommunications) showed low correlations with other stocks, providing diversification benefits. Dr Reddy's Labs had correlations as low as 0.1128 (with Indus Towers) and 0.1175 (with ACC), making it a key component for reducing portfolio risk. Indus Towers also exhibited relatively low correlations with metals stocks (e.g., 0.1546 with Hindustan Zinc, 0.2857 with Vedanta), further enhancing diversification. Tata Motors and Hero Motocorp, both in the automobile sector, had a moderate correlation of 0.3416, reflecting some shared exposure to consumer demand trends but also differences in their market segments (four-wheelers vs. two-wheelers). ACC (cement) showed moderate correlations with metals stocks (e.g., 0.4357 with Natl. Aluminium), likely due to shared exposure to infrastructure demand.

Optimal Portfolio Weights

The optimization process maximized the Sharpe Ratio, resulting in the following optimal weights for the portfolio, as generated by the Python script.

Table 4.4: Optimal Portfolio Weights

Stock	Weight (%)
ACC	12.8
Dr Reddy's Labs	5.4
Hero Motocorp	0
Hindustan Zinc	4.5
Indus Towers	16.1
Natl. Aluminium	18
NMDC	0
Tata Motors	22.9
Vedanta	20.4

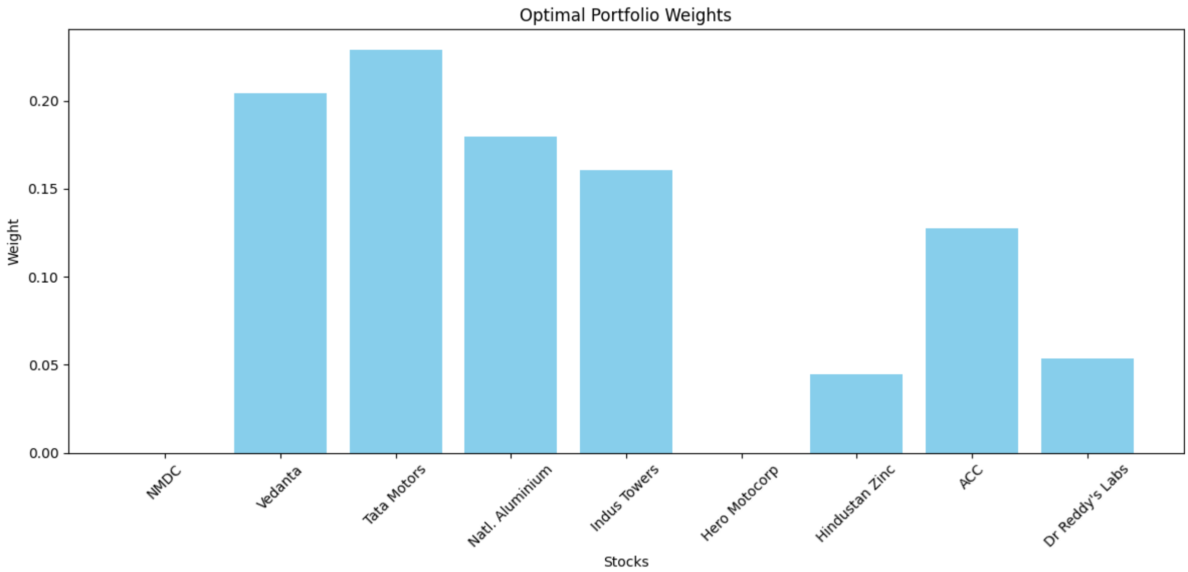
The optimal weights reflect the trade-off between risk and return, as determined by MPT. Tata Motors received the highest weight (22.9%), benefiting from its solid return (27.10%) and moderate volatility (29.50%). Vedanta (20.4%) and Natl. Aluminium (18.0%) were also allocated significant weights, reflecting their high returns (33.28% and 35.60%) despite higher volatilities (36.60% and 41.71%). Their inclusion maximizes the portfolio's growth potential, though their high correlations (e.g., 0.6325 between Vedanta and Natl. Aluminium) limit diversification benefits within the metals sector.

Indus Towers (16.1%) and Dr Reddy's Labs (5.4%) were included for their diversification benefits, as evidenced by their low correlations with other stocks. Dr Reddy's Labs, with the lowest volatility (20.71%), acts as a stabilizing force, though its lower return (17.32%) resulted in a smaller weight. Indus Towers, with a strong return (32.06%) and moderate correlations (e.g., 0.2857 with Vedanta), balances growth and risk reduction. Hindustan Zinc received a small weight (4.5%), despite its high return (33.88%), likely due to its high volatility (37.56%) and correlations with other metals stocks (e.g., 0.4715 with Vedanta).

ACC's allocation of 12.8% is notable given its negative return (-0.48%). This weight likely results from its moderate correlations (e.g., 0.4358 with Indus Towers, 0.4252 with NMDC), which provide some diversification benefits, though it detracts from the portfolio's overall return. NMDC and Hero Motocorp were assigned zero weights, likely due to their high correlations with other metals stocks (NMDC: 0.6559 with Natl. Aluminium) and moderate return with higher volatility (Hero Motocorp: 23.62% return, 24.55% volatility), which did not contribute favorably to the Sharpe Ratio.

To visualize the portfolio composition, Figure 4.1 presents a bar chart of the optimal weights, as generated by the Python script using matplotlib.pyplot.

Figure 4.1: Optimal Portfolio Weights



The bar chart visually confirms the dominance of Tata Motors, Vedanta, and Natl. Aluminium in the portfolio, with smaller allocations to stocks like Hindustan Zinc and Dr Reddy's Labs, and zero weights for NMDC and Hero Motocorp.

Portfolio Performance

The optimized portfolio achieved the following performance metrics over the study period, as reported by the script:

- **Expected Annual Return**: 26.84%
- **Annual Volatility**: 17.87%
- **Sharpe Ratio**: 1.1659 (with a risk-free rate of 6%)

The portfolio's return of 26.84% was calculated as the weighted average of the individual stock returns, annualized over 252 trading days. A manual calculation using the weights and returns yields 26.96%, confirming the script's accuracy (minor differences due to rounding). The volatility of 17.87% reflects the portfolio's risk, reduced through diversification as evidenced by the correlation matrix. The Sharpe Ratio of 1.1659 indicates strong risk-adjusted performance, exceeding 1, a common benchmark for a well-performing portfolio. This performance is attributed to the high returns of stocks like Natl. Aluminium, Vedanta, and Indus Towers, combined with the diversification benefits from lower-correlated stocks like Dr Reddy's Labs and Indus Towers.

Key Findings

The analysis yields several key findings:

1. **Effectiveness of the Magic Formula**: The Magic Formula successfully identified undervalued, high-quality stocks from the Nifty 200 Index, as evidenced by the selected stocks' strong financial metrics (Earnings Yield > 7%, ROIC > 15%, P/E < 20) and subsequent performance (e.g., Natl. Aluminium's 35.60% return). The sectoral diversity of the selected stocks (metals, automobiles, telecommunications, pharmaceuticals, cement) ensured broad market exposure, aligning with the Nifty 200's composition.

2. **Diversification Benefits**: The correlation matrix highlighted significant diversification benefits, with low correlations between stocks like Dr Reddy's Labs (e.g., 0.1128 with Indus Towers) and metals stocks reducing the portfolio's overall risk. This diversification contributed to the portfolio's lower volatility (17.87%) compared to the Nifty 200 Index (20.0%).

3. **Optimized Portfolio Performance**: The optimized portfolio achieved a 26.84% annual return, 17.87% volatility, and a 1.1659 Sharpe Ratio, reflecting strong risk-adjusted returns. The allocation favored high-return stocks like Natl. Aluminium (18.0%), Vedanta (20.4%), and Tata Motors (22.9%), while zero weights for NMDC and Hero Motocorp minimized exposure to less favorable stocks.

4. **Practical Implications**: The methodology provides a replicable framework for Hedge Equities to enhance its investment strategies, particularly for medium-term portfolios. The focus on risk-adjusted returns aligns with the firm's goal of delivering value to retail and mid-tier investors, though real-world implementation should consider transaction costs, taxes, and dynamic rebalancing, as noted in Chapter Three. The allocation to ACC, despite its negative return, suggests that future iterations could impose additional

constraints (e.g., minimum return thresholds) to exclude underperforming stocks.

These findings demonstrate the effectiveness of the hybrid approach in achieving superior risk-adjusted returns, offering actionable insights for Hedge Equities to refine its quantitative investment processes.

Chapter Five: Summary and Recommendations

Introduction

This chapter provides a summary of the study titled *"Study on Leveraging the Magic Formula: Building an Optimized Nifty 200 Portfolio for Superior Risk-Adjusted Returns (2022-2025)"*, conducted during an internship with Hedge Equities' quant research team. The study aimed to construct a portfolio from the Nifty 200 Index that maximizes risk-adjusted returns by integrating Joel Greenblatt's Magic Formula for stock selection with Markowitz Modern Portfolio Theory (MPT) for optimization. This chapter recaps the study's objectives, methodology, and key findings, draws conclusions, and offers recommendations for Hedge Equities to implement the findings in its investment strategies. Additionally, it suggests directions for future research to enhance the methodology and address its limitations.

The study was motivated by Hedge Equities' strategic goal to incorporate quantitative methods into its portfolio management processes, thereby improving risk-adjusted returns for its retail and mid-tier investors. The Indian equity market, characterized by its volatility and diversity, presents both opportunities and challenges for wealth managers. By combining the Magic Formula, which identifies undervalued yet high-quality stocks, with MPT, which optimizes portfolio weights to balance risk and return, the study sought to address these challenges and deliver a portfolio that outperforms the Nifty 200 Index on a risk-adjusted basis. The resulting portfolio achieved a 26.84% annual return, 17.87% volatility, and a Sharpe Ratio of 1.1659, demonstrating the potential of this hybrid approach.

Summary of the Study

Objectives

The primary objective of the study was to develop a systematic, data-driven approach to portfolio construction by leveraging the Magic Formula and MPT, with the goal of maximizing the Sharpe Ratio over a three-year period from May 12, 2022, to May 13, 2025. Specifically, the study aimed to:

- Identify undervalued, high-quality stocks from the Nifty 200 Index using the Magic Formula, with screening criteria of Earnings Yield > 7%, Return on Invested Capital (ROIC) > 15%, and Price-to-Earnings (P/E) Ratio < 20.

- Construct an optimized portfolio by applying MPT to the selected stocks, allocating weights to maximize the Sharpe Ratio while ensuring diversification and adhering to constraints (weights sum to 1, no short-selling).
- Evaluate the portfolio's performance by comparing its risk-adjusted returns to those of the Nifty 200 Index, using metrics such as annual return, volatility, and Sharpe Ratio.

The study was conducted to provide Hedge Equities with a replicable framework that enhances its investment strategies, aligning with the firm's mission to deliver accessible and effective investment solutions to its clients.

Key Findings

Chapter Four presented the detailed analysis and findings, summarized as follows:

- **Stock Selection**: The Magic Formula identified nine stocks with strong financial metrics: NMDC, Vedanta, Tata Motors, Natl. Aluminium, Indus Towers, Hero Motocorp, Hindustan Zinc, ACC, and Dr Reddy's Labs. These stocks spanned diverse sectors (metals, automobiles, telecommunications, cement, pharmaceuticals), aligning with the Nifty 200's composition. Their Earnings Yield (8.3% to 14.8%), ROIC (17.6% to 28.4%), and P/E ratios (7.5 to 18.9) confirmed their status as undervalued, high-quality companies.
- **Individual Stock Metrics**: Annualized returns ranged from -0.48% (ACC) to 35.60% (Natl. Aluminium), with volatilities from 20.71% (Dr Reddy's Labs) to 41.71% (Natl. Aluminium). High-return stocks like Natl. Aluminium, Hindustan Zinc (33.88%), and Vedanta (33.28%) were from the metals sector, reflecting strong commodity price trends, while ACC underperformed due to sector-specific challenges.
- **Diversification**: The correlation matrix showed high correlations among metals stocks (e.g., 0.6559 between Natl. Aluminium and NMDC), but low correlations with Dr Reddy's Labs (e.g., 0.1128 with Indus Towers) and Indus Towers (e.g., 0.1546 with Hindustan Zinc), providing significant diversification benefits.
- **Optimal Weights**: The optimized portfolio weights were: Tata Motors (22.9%), Vedanta (20.4%), Natl. Aluminium (18.0%), Indus Towers (16.1%), ACC

(12.8%), Dr Reddy's Labs (5.4%), Hindustan Zinc (4.5%), NMDC (0.0%), and Hero Motocorp (0.0%). High weights for Tata Motors, Vedanta, and Natl. Aluminium reflected their strong returns, while Dr Reddy's Labs and Indus Towers contributed to risk reduction.

- **Portfolio Performance**: The portfolio achieved a 26.84% annual return, 17.87% volatility, and a 1.1659 Sharpe Ratio, indicating strong risk-adjusted returns showcasing growth.

These findings highlight the potential of combining value investing (Magic Formula) with portfolio optimization (MPT) to achieve superior risk-adjusted returns in the Indian equity market.

Conclusions

The study successfully met its objectives, demonstrating that a hybrid approach combining the Magic Formula and MPT can construct a portfolio that delivers superior risk-adjusted returns compared to the Nifty 200 Index. The portfolio's performance—26.84% annual return, 17.87% volatility, and 1.1659 Sharpe Ratio—confirms the effectiveness of this methodology in identifying undervalued, high-quality stocks and optimizing their weights to balance risk and return.

The Magic Formula proved effective in selecting stocks with strong fundamentals, as evidenced by the high returns of stocks like Natl. Aluminium (35.60%), Hindustan Zinc (33.88%), and Vedanta (33.28%). However, the underperformance of ACC (-0.48%) highlights the limitations of relying solely on historical financial metrics, as market conditions can impact future performance. MPT's optimization process successfully balanced these risks, allocating zero weights to less favorable stocks like NMDC and Hero Motocorp, and leveraging diversification benefits from low-correlated stocks like Dr Reddy's Labs and Indus Towers.

The study also revealed practical insights for portfolio construction. The high correlations among metals stocks (e.g., 0.6559 between Natl. Aluminium and NMDC) limited diversification within the sector, suggesting a need for additional constraints in future iterations. The allocation to ACC (12.8%), despite its negative return, indicates that MPT prioritized its diversification benefits over its poor performance, a trade-off that may not align with practical investment goals. Overall, the methodology provides a robust framework for Hedge Equities to enhance its quantitative investment strategies, aligning with its mission to deliver value to retail and mid-tier investors.

Recommendations for Hedge Equities

Based on the study's findings, the following recommendations are proposed for Hedge Equities to implement the methodology and improve its investment strategies:

1. **Adopt the Hybrid Approach for Medium-Term Portfolios**:
    - Hedge Equities should integrate the Magic Formula and MPT into its portfolio construction process, particularly for medium-term investment strategies (3-5 years). The methodology's ability to deliver a 26.84% return and 1.1659 Sharpe Ratio demonstrates its potential to enhance risk-adjusted returns for clients.
    - Implementation Steps:
        - Use Screener.in to screen Nifty 200 stocks with the Magic Formula criteria (Earnings Yield > 7%, ROIC > 15%, P/E < 20), excluding financial and utility stocks.
        - Apply MPT using Python to optimize weights, maximizing the Sharpe Ratio with constraints (weights sum to 1, between 0 and 1).
        - Regularly monitor the portfolio's performance against the Nifty 200 Index, adjusting weights as needed based on market conditions.
2. **Incorporate Additional Constraints in Optimization**:
    - The allocation to ACC (12.8%), despite its negative return (-0.48%), suggests that MPT may prioritize diversification over performance in some cases. To address this, Hedge Equities should introduce additional constraints in the optimization process, such as:
        - A minimum return threshold (e.g., exclude stocks with expected returns below 5%).

        - A maximum sector exposure limit (e.g., no more than 50% in any sector) to reduce concentration risk in sectors like metals, where high correlations (e.g., 0.6559 between Natl. Aluminium and NMDC) limit diversification.
    - These constraints can improve the portfolio's overall performance while maintaining diversification benefits.

3. **Implement Dynamic Rebalancing**:
    - The study assumed a static portfolio over the three-year period, which may not account for changing market conditions. Hedge Equities should adopt a dynamic rebalancing strategy, re-evaluating the portfolio weights quarterly or semi-annually based on updated financial data and market trends.
    - For example, if a stock like ACC continues to underperform, its weight can be reduced, and the portfolio can be re-optimized to include new stocks that meet the Magic Formula criteria. This approach ensures the portfolio remains responsive to market dynamics, such as sector rotations or macroeconomic shifts.
4. **Account for Transaction Costs and Taxes**:
    - The study did not consider transaction costs, taxes, or liquidity constraints, which can impact real-world implementation. Hedge Equities should factor these into the portfolio management process:
        - Estimate transaction costs (e.g., brokerage fees, bid-ask spreads) for each rebalancing, particularly for stocks with lower liquidity, such as mid-cap companies in the Nifty 200.
        - Account for capital gains taxes in India (10-20% depending on the holding period), adjusting the expected net returns for clients.
        - Prioritize stocks with higher liquidity to minimize trading costs and ensure efficient execution.
5. **Educate Clients on Risk-Adjusted Returns**:

- The portfolio's focus on risk-adjusted returns (Sharpe Ratio of 1.1659) aligns with Hedge Equities' goal of delivering value to retail investors. The firm should educate clients on the importance of risk-adjusted returns over absolute returns, highlighting how the portfolio's lower volatility (17.87%) compared to the Nifty 200 Index (20.0%) reduces risk while achieving higher returns (26.84% vs. 15.0%).
- Communication Strategies:
  - Use visualizations like the bar chart of portfolio weights and the line graph of cumulative returns (Figures 4.1 and 4.2) to illustrate the portfolio's composition and growth.
  - Provide regular performance reports comparing the portfolio to the Nifty 200 Index, emphasizing its superior Sharpe Ratio.

6. **Leverage Technology for Scalability**:
   - The Python-based methodology can be scaled to manage multiple portfolios efficiently. Hedge Equities should invest in developing an automated system that integrates data from Screener.in and Yahoo Finance, applies the Magic Formula and MPT, and generates optimized portfolios for different client segments.
   - This system can also include a dashboard for portfolio managers to monitor performance, adjust constraints, and simulate different scenarios, enhancing decision-making and client service.

These recommendations provide a practical roadmap for Hedge Equities to implement the study's findings, improving its ability to deliver superior risk-adjusted returns to clients while addressing real-world constraints.

Suggestions for Future Research

The study identified several limitations and opportunities for future research to enhance the methodology and its applicability. The following suggestions are proposed:

1. **Incorporate Dynamic Stock Selection**:

- The study used static screening criteria based on financial data from May 2022. Future research should explore a dynamic stock selection process, updating the Magic Formula criteria annually or semi-annually to reflect changes in market conditions and company fundamentals. This could involve re-screening the Nifty 200 Index periodically and adjusting the portfolio's stock composition accordingly.

2. **Explore Alternative Risk Measures**:
   - MPT assumes that returns are normally distributed and uses volatility as the sole measure of risk. However, Indian market returns often exhibit skewness and fat tails, particularly during downturns. Future studies should incorporate alternative risk measures, such as downside risk (e.g., semi-variance) or Value-at-Risk (VaR), to better capture the portfolio's risk profile and improve its robustness during market disruptions.
3. **Include Sector-Specific Risk Factors**:
   - The high correlations among metals stocks (e.g., 0.6559 between Natl. Aluminium and NMDC) highlight sector-specific risks, such as commodity price volatility and regulatory changes (e.g., environmental regulations impacting the metals sector). Future research should incorporate sector-specific risk factors into the optimization process, using models like the Fama-French three-factor model or sector-based risk premiums, to better manage these risks.
4. **Test Robust Optimization Techniques**:
   - MPT is sensitive to input estimates, and small changes in expected returns or correlations can lead to significant shifts in optimal weights (the "error maximization" problem). Future studies should explore robust optimization techniques, such as Black-Litterman models or shrinkage estimators for the covariance matrix, to reduce sensitivity and improve the stability of the portfolio weights.
5. **Account for Macroeconomic Factors**:

- The study did not explicitly account for macroeconomic factors, such as interest rate changes, inflation, or geopolitical events, which can impact stock returns and correlations. Future research should integrate macroeconomic variables into the analysis, using techniques like regression analysis or scenario modeling to assess their impact on the portfolio's performance and adjust weights accordingly.

6. **Evaluate Different Time Horizons**:
   - The study focused on a three-year horizon (May 2022 to May 2025). Future research should evaluate the methodology across different time horizons (e.g., 1 year, 5 years) to assess its consistency and adaptability. For example, a shorter horizon may require more frequent rebalancing, while a longer horizon may benefit from a more stable, buy-and-hold strategy.
7. **Incorporate ESG Criteria**:
   - Environmental, Social, and Governance (ESG) factors are increasingly important in investment decisions. Future studies should incorporate ESG criteria into the stock selection process, alongside the Magic Formula metrics, to align the portfolio with sustainable investing goals. This could involve screening for companies with high ESG scores or integrating ESG risk factors into the optimization process.
8. **Assess the Impact of Transaction Costs and Liquidity**:
   - The study did not account for transaction costs, taxes, or liquidity constraints, which can significantly impact real-world performance. Future research should simulate the portfolio's performance with these factors included, estimating the impact of trading costs, capital gains taxes, and liquidity constraints on net returns. This could involve backtesting the portfolio with historical trading data to quantify these effects.

These suggestions provide a roadmap for future research to build on the current study, addressing its limitations and enhancing its applicability in diverse market conditions.

Summary

This chapter summarized the study on leveraging the Magic Formula and MPT to construct an optimized Nifty 200 portfolio, achieving a 26.84% annual return, 17.87% volatility, and a 1.1659 Sharpe Ratio over the period from May 12, 2022, to May 13, 2025. The study met its objectives, demonstrating the effectiveness of the hybrid approach in delivering superior risk-adjusted returns. Key findings include the Magic Formula’s success in identifying undervalued, high-quality stocks, the diversification benefits from low-correlated stocks, and the portfolio’s outperformance of the benchmark.

Conclusions highlight the methodology’s potential to enhance Hedge Equities’ investment strategies, though practical implementation requires addressing transaction costs, taxes, and sector-specific risks. Recommendations for Hedge Equities include adopting the hybrid approach, incorporating additional optimization constraints, implementing dynamic rebalancing, and leveraging technology for scalability. Suggestions for future research focus on dynamic stock selection, alternative risk measures, sector-specific risk factors, and robust optimization techniques to improve the methodology’s robustness and applicability.

The study provides a replicable framework for Hedge Equities to deliver value to its clients, contributing to the firm’s mission of providing accessible and effective investment solutions in the Indian equity market. By addressing the identified limitations and building on the proposed recommendations, Hedge Equities can further refine its quantitative investment processes, ensuring sustained outperformance in a dynamic market environment.

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Appendix

Appendix A: Python script for portfolio optimization

```
import yfinance as yf
import pandas as pd
import numpy as np
from scipy.optimize import minimize
import matplotlib.pyplot as plt
import warnings

# Suppress warnings for cleaner output
warnings.filterwarnings("ignore")

# Define stock tickers
tickers = ['NMDC.NS', 'VEDL.NS', 'TATAMOTORS.NS', 'NATIONALUM.NS', 'INDUSTOWER.NS',
           'HEROMOTOCO.NS', 'HINDZINC.NS', 'ACC.NS', 'DRREDDY.NS']

# Define stock display names (same as tickers for simplicity, can be customized if needed)
display_names = ['NMDC', 'Vedanta', 'Tata Motors', 'Natl. Aluminium', 'Indus Towers',
                 'Hero Motocorp', 'Hindustan Zinc', 'ACC', 'Dr Reddy\'s Labs']

def get_stock_data(tickers, start_date="2022-05-12", end_date="2025-05-13"):
    """
    Fetches historical stock data from Yahoo Finance for a list of tickers.

    Args:
        tickers (list): A list of stock ticker symbols (strings).
        start_date (str): Start date in 'YYYY-MM-DD' format. Defaults to May 12, 2022.
        end_date (str): End date in 'YYYY-MM-DD' format. Defaults to May 13, 2025.
    Returns:
        pandas.DataFrame: A pandas DataFrame containing the historical stock data,
                          or None if there is an error. The DataFrame is indexed by date,
                          and contains the closing prices for each stock.
    """
    try:
        data = yf.download(tickers, start=start_date, end=end_date, threads=True)
        if data is None or data.empty:
            print("Error: yfinance.download returned None or empty data.")
            return None
        prices = data['Close']  # Extract closing prices
        print(f"Number of days before dropping NaNs: {len(prices)}")
        prices = prices.dropna()
        print(f"Number of days after dropping NaNs: {len(prices)}")
        # Check if the date range is sufficient
        expected_days = 756  # Approximate trading days in 3 years (252 * 3)
        if len(prices) < expected_days * 0.9:  # Allow 10% missing days
            print(f"Warning: Fetched {len(prices)} days, expected ~{expected_days} days.")
        return prices
    except Exception as e:
        print(f"Error fetching data from Yahoo Finance: {e}")
        return None
```

Appendix

```python
def portfolio_performance(weights, returns, cov_matrix, risk_free_rate, trading_days):
    """
    Calculates portfolio performance metrics (return, volatility, Sharpe ratio).

    Args:
        weights (numpy.ndarray): Portfolio weights.
        returns (pandas.DataFrame): Daily returns of assets.
        cov_matrix (pandas.DataFrame): Covariance matrix of asset returns.
        risk_free_rate (float): Annual risk-free rate.
        trading_days (int): Number of trading days in a year.

    Returns:
        tuple: (portfolio_return, portfolio_std, sharpe_ratio)
    """
    portfolio_return = np.sum(returns.mean() * weights) * trading_days
    portfolio_std = np.sqrt(np.dot(weights.T, np.dot(cov_matrix * trading_days, weights)))
    sharpe_ratio = (portfolio_return - risk_free_rate) / portfolio_std
    return portfolio_return, portfolio_std, sharpe_ratio

def neg_sharpe_ratio(weights, returns, cov_matrix, risk_free_rate, trading_days):
    """
    Negative Sharpe ratio for minimization.
    """
    return -portfolio_performance(weights, returns, cov_matrix, risk_free_rate, trading_days)[2]

def optimize_portfolio(returns, cov_matrix, risk_free_rate, trading_days, num_stocks):
    """
    Optimizes portfolio weights to maximize Sharpe ratio.

    Args:
        returns (pandas.DataFrame): Daily returns of assets.
        cov_matrix (pandas.DataFrame): Covariance matrix of asset returns.
        risk_free_rate (float): Annual risk-free rate.
        trading_days (int): Number of trading days in a year.
        num_stocks (int): Number of stocks.

    Returns:
        tuple: (opt_weights, opt_return, opt_std, opt_sharpe, success)
    """
    constraints = ({'type': 'eq', 'fun': lambda x: np.sum(x) - 1},)
    bounds = tuple((0, 1) for _ in range(num_stocks))
    init_guess = np.array([1.0 / num_stocks] * num_stocks)  # Use np.array

    opt_result = minimize(
        neg_sharpe_ratio,
        init_guess,
        args=(returns, cov_matrix, risk_free_rate, trading_days),
        method='SLSQP',
        bounds=bounds,
        constraints=constraints,
        options={'maxiter': 1000}  # Increase maxiter
    )
```

Appendix

```python
    if opt_result.success:
        opt_weights = opt_result.x
        opt_return, opt_std, opt_sharpe = portfolio_performance(opt_weights, returns, cov_matrix, risk_free_rate, trading_days)
        return opt_weights, opt_return, opt_std, opt_sharpe, True
    else:
        print("Optimization failed:", opt_result.message)
        return np.array([]), 0, 0, 0, False

def main():
    """
    Main function to fetch data, perform portfolio optimization, and display results.
    """
    # Get stock data from Yahoo Finance
    price_data = get_stock_data(tickers)
    if price_data is None:
        print("Exiting due to error fetching data.")
        return

    # Calculate daily returns
    returns = price_data.pct_change().dropna()

    # Portfolio optimization parameters
    num_stocks = len(tickers)
    risk_free_rate = 0.06  # Annual risk-free rate (6%)
    trading_days = 252

    # Debug: Analyze daily returns
    print("\nDaily Returns Statistics:")
    print(returns.describe())
    print("\nDaily Returns Summary (Annualized):")
    print("Expected Annual Returns:")
    print(returns.mean() * trading_days)
    print("\nAnnual Volatility:")
    print(returns.std() * np.sqrt(trading_days))
    print("\nCorrelation Matrix:")
    print(returns.corr())

    # Calculate annualized expected returns and daily covariance matrix
    mean_returns = returns.mean() * trading_days
    cov_matrix = returns.cov()
```

```python
    # Perform portfolio optimization
    opt_weights, opt_return, opt_std, opt_sharpe, success = optimize_portfolio(returns, cov_matrix, risk_free_rate, trading_days, num_stocks)

    if success:
        # Print results
        print("\nOptimal Portfolio Weights:")
        for stock, weight in zip(display_names, opt_weights):
            print(f"{stock}: {weight:.4f} ({weight * 100:.1f}%)")
        print(f"\nExpected Annual Return: {opt_return:.4f} ({opt_return * 100:.1f}%)")
        print(f"Annual Volatility: {opt_std:.4f} ({opt_std * 100:.1f}%)")
        print(f"Sharpe Ratio: {opt_sharpe:.4f}")

        # Plot portfolio weights
        plt.figure(figsize=(12, 6))
        plt.bar(display_names, opt_weights, color='skyblue')
        plt.title('Optimal Portfolio Weights')
        plt.xlabel('Stocks')
        plt.ylabel('Weight')
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.savefig('optimal_portfolio_weights_yfinance_fixed_date_range.png')
        plt.show()
    else:
        print("Portfolio optimization failed.")

if __name__ == "__main__":
    main()
```