

Louvain School of Management

A Comparative Analysis of Fundamental and Technical Investment Strategies: Empirical Evidence from the S&P 500 2021–2025

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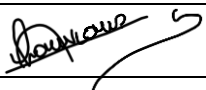
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Summary

Investing in finance is a dynamic and sophisticated field of endeavor where picking the right strategy will make the difference between generating sustained returns and eroding capital. In fact, the key challenge faced by portfolio managers and investors in general is finding investment methods that have strong theoretical underpinnings and empirical validation under diverse market circumstances. Such is the challenge tackled in this thesis.

A comparison between two different investment strategies is carried out in this study using S&P 500 stocks in the period of 2021-2025: a fundamental buy and hold strategy using screening criteria to identify undervalued stocks according to value investing principles, and a technical method using moving averages crossover rules for trading. The main difference between these two strategies is in the underlying rationale and the process through which each is applied. Specifically, the fundamental buy and hold strategy uses the valuation of stocks, identifying those companies with favorable economic fundamentals such as low P/E ratios, increasing earnings, and appropriate levels of debt, in accordance with Damodaran (2012) and Fama and French (1992). The second relies exclusively on price signals, entering positions upon a Golden Cross and exiting upon a Death Cross, as documented by Brock et al. (1992) and Lo et al. (2000).

An important methodological innovation made by this thesis involves the implementation of both approaches on exactly the same portfolio of stocks every year. In this way, the impact of the investing approach used is isolated and unaffected by possible distortions introduced due to different portfolios being used. This experimental setup provides for a much more thorough comparison of performance than those seen in other research works.

From an empirical standpoint, there are notable distinctions between the two methods. While the fundamental approach proves superior in regard to performance, both absolute and risk-adjusted, over a longer period of time, the technical approach produces better results when it comes to preserving capital, displaying lower volatility as well as a lower maximum drawdown compared to the other method.

Importantly, the performance of the two approaches differs significantly based on the market environment, and this finding fully supports the Adaptive Markets Hypothesis proposed by Lo (2004). Specifically, the fundamental approach proves more effective during bull markets while the technical one prevails in bear market conditions as a result of lower risk-taking. As far as economic alpha is concerned, neither of the two methods produces statistically significant results as compared to a passive investment strategy over the entire period examined, thus corroborating the semi-strong Efficient Market Hypothesis.

Overall, this dissertation has shown that fundamental analysis and technical analysis do not represent opposing approaches to investing but are rather complementary approaches to investing based on market conditions. These findings pave the way for future research into investment approaches that use the risk-reducing aspects of trend trading along with the returns generated by value investing.

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The fact of completing my thesis carries a special meaning because by doing so I have been able to delve into the study of an area that has always attracted me since its very beginnings and which I now strive to become a professional in: investments and portfolio management. The opportunity of discovering my true vocation, acquiring the means to make a profession out of it, and laying down the groundwork for my professional life would not be possible without my studies at UCLouvain. I am sincerely thankful for this to both the university and to all the professors who taught me during this time.

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1. Introduction

1.1 Context of the study

The evolution of the finance sector in recent decades has offered portfolio managers various methods of investment (Lo, 2004; Shiller, 2003). Among the many, two techniques are very popular but are quite different from each other in terms of theory and approach to investment. These techniques include fundamental analysis and technical analysis. For instance, when it comes to fundamental analysis, the valuation process of assessing the intrinsic value of the firm is done using the financial statement of the company with respect to their earnings, profits, and cash flows (Damodaran, 2012; Ball & Brown, 1968). For that reason, some traditional approaches to this form of analysis include Discounted Cash Flow Model and financial ratios like P/E Ratio and ROE (Damodaran, 2012). However, in regard to technical analysis, the purpose of the analysis would be to observe the trend of stocks from previous prices and volume data (Brock et al., 1992; Lo et al., 2000). Some of the commonly used tools would include Moving Average and RSI.

The issue of whether one approach outperforms the other remains unresolved in the academic literature. According to Efficient Market Hypothesis (EMH), stock prices reflect all available information, which makes making money using either method unlikely (Fama, 1970). Conversely, the theory of behavioral finance argues that financial markets are illogical and can be utilized by investors to make profit (Shiller, 2003; Barberis et al., 1998). Furthermore, according to Adaptive Markets Hypothesis proposed by Lo in 2004, the efficiency of any approach depends on the state of the market at any point in time. This unresolved issue becomes a clear basis for empirical study.

This comparison is particularly suitable for the period 2021–2025. It includes the sharp market decline following the COVID-19 pandemic, a strong rebound fuelled by monetary policy, a period of high inflation and a cycle of interest rate increases. This evolving set of market regimes presents a particularly suitable setting in which to study not only which approach performs better overall, but also under which specific conditions each strategy holds an advantage.

In essence, there are two key contributions that this thesis seeks to make to the current body of literature. The first is providing an empirical study that compares fundamental and technical investment approaches while considering real-life issues such as transaction costs and liquidity. The second contribution of the thesis is in providing practical implications for portfolio managers when making decisions amid uncertainty in the financial market.

1.2 Motivation

Academic literature is far from conclusive about whether fundamental or technical analysis delivers better performance. The efficient market hypothesis suggests that markets are efficient and therefore the added value of any active strategy is challenged (Fama, 1970; Fama & French, 2010), while some other studies find persistent patterns in price behavior indicating markets are not always fully rational (Jegadeesh & Titman, 1993; Barberis et al., 1998). This lack of consensus is what motivates this study.

Apart from the theoretical debate, there are clear practical ramifications of this question, as every portfolio manager or investor faces the task of selecting a strategy that is both theoretically sound and applicable under practical conditions. This particular period from 2021

to 2025 has been characterized by a crash due to the coronavirus pandemic, a recovery period, high inflation, and increasing interest rates, making each stage more suited to one investment strategy over another.

This thesis is also driven by another gap within the available literature. The vast majority of studies that have been conducted in regard to fundamental and technical analysis have focused on assessing the effectiveness of each methodology separately without using both methodologies for the evaluation of the same set of securities under identical conditions. As a result, conducting comparisons based on the findings can be complicated due to the fact that any divergence in results may be caused not by the difference between the approaches but rather by the discrepancy in portfolio construction.

1.3 Research questions

What is the performance of a buy-and-hold portfolio constructed on fundamental criteria relative to the performance of a technically timed portfolio applied to the same set of securities during the period 2021–2025? This is the central research question of this thesis.

This question is answered by exploring three sub-questions. First, which of the strategies yields higher risk-adjusted returns over the entire study period in terms of the Sharpe ratio, Sortino ratio and maximum drawdown? Secondly, what is the relative performance of each strategy as a function of the market conditions, for example, recovery from crisis (2021-2022) or high interest rate environment (2023-2025)? Third, do the results support the Efficient Market Hypothesis or a behavioral finance interpretation?

In this thesis, I use a number of theoretical frameworks to address these questions. Both strategies are tested based on the theoretical background of the Efficient Market Hypothesis (Fama, 1970). Any performance differences that may be observed can be alternatively explained by behavioral finance (Shiller, 2003; Barberis et al., 1998). Lo (2004) proposed the Adaptive Markets Hypothesis which states that the effectiveness of each strategy might differ depending on the market environment, which is particularly relevant because of the multiple regimes within the study period. Performance is measured using the commonly used risk-adjusted performance measures such as the Sharpe Ratio (Sharpe, 1966), Sortino Ratio (Sortino & van der Meer, 1991), and maximum drawdown in the portfolio context as presented by Markowitz (1952).

The results of the current study have practical significance not only for academia but also for practitioners. Theoretically, the comparison helps clarify under which conditions the advantage of fundamental or technical analysis is valid, and whether the results are better explained by market efficiency or behavioral factors. From a practical standpoint the results provide directions to portfolio managers who need to adapt their strategies to changing market conditions. The study also contributes to the existing literature by applying both strategies to the same controlled portfolio universe and by outlining avenues for further research, especially around hybrid strategies combining the two approaches.

1.4 Overview of the methodology

This thesis adopts a quantitative approach based on historical market data covering the 2021–2025 period. The starting universe consists of the S&P 500, from which approximately 20 securities are selected each year through a three-step screening process. First, the top 10% and

bottom 10% of companies by market capitalization are excluded to avoid the distortions associated with the largest and smallest companies within the index, as documented by Fama & French (1992). Second, the remaining companies are filtered using fundamental criteria: a positive ROE, a debt-to-equity ratio below 1.5, and positive earnings growth over the previous year. Third, from the companies that pass these filters, those with the lowest P/E ratios (roughly the bottom 30% to 40%) are selected to form the final portfolio of approximately 20 securities, in line with the value investing framework described by Damodaran (2012). The portfolio is rebalanced annually to reflect updated financial data.

Both of these methods are used on exactly the same stocks. This means that the portfolios will be the same in terms of the securities involved, the only thing that will vary is how each of the methods deals with entry and exit from trades. While the fundamental method simply involves buying and holding the chosen stocks throughout the year, the technical method employs the same stocks, using Moving Average crossover to determine entries and exits, buying when the MA50 crosses above the MA100 and selling when it crosses below the MA100, while the RSI is used as a complementary momentum indicator to support the interpretation of market conditions, a method outlined first by Brock et al. (1992) and enhanced by Lo et al. (2000).

1.5 Summary of empirical results

The empirical results reveal important differences between the fundamental and technical investment strategies over the 2021–2025 period. Overall, the fundamental buy-and-hold strategy generated stronger long-term performance, with higher average annual returns and superior risk-adjusted metrics than the technical MA50/MA100 crossover strategy. These findings support the view that value-oriented stock selection remains effective over extended investment horizons.

However, the technical strategy demonstrated clear advantages in terms of downside protection and volatility reduction. The technical method added value in negative market phases, especially in 2022, by reducing market exposure after signals of a bearish trend, and limited market participation in the market decline. By contrast, the fundamental strategy did best in strong bull market environments, such as 2021 and 2023, when being fully invested let the portfolio participate in the upside appreciation of equities.

Thus, the results are strongly in favour of Lo's (2004) Adaptive Markets Hypothesis, indicating that the relative effectiveness of each strategy is dependent on the market regime in place, and not that one methodology consistently dominates the other.

At the same time, both strategies underperformed the SPY benchmark over the full sample period, which is broadly consistent with the Efficient Market Hypothesis and the existing literature on the difficulty of generating persistent excess returns after costs.

Finally, the analysis shows that while the fundamental strategy offers stronger return generation, the technical strategy provides meaningful benefits in terms of capital preservation and drawdown reduction. The findings therefore suggest that the two methodologies may be complementary rather than strictly competing approaches.

2. Conceptual framework

2.1 Equity funds

Equity funds are also considered as investment vehicles where the amount of funds pooled together by many investors is primarily invested in purchasing shares from publicly listed firms, thereby making the investors owners of the portfolio consisting of the various asset classes managed professionally (Ferreira et al., 2013). The value of the equity funds is derived based on their NAV (Net Asset Value), which refers to the sum total of the value of assets minus the liabilities (fees for management and administration, withdrawals, etc.) divided by the total number of outstanding shares. Profits may come from the increase in value of the stocks or the dividends received by companies where the stocks have been bought through the equity fund. In order to conduct comparative analysis in this study, an artificial equity portfolio will be considered.

Theory of equity mutual funds is closely connected to the modern portfolio theory. As Markowitz stated in 1952, diversification between several stocks lessens non-systematic risk. This theory has been applied to the operation of mutual funds, which include various investments in different areas, industries, and geographical locations to assist investors in minimizing their unsystematic risks. Market efficiency is another feature that may be related to the operation of mutual funds. Fama claimed that information is already reflected in the price of stocks, and there is no possibility for an investor to receive abnormal returns by using active investment strategy. In turn, behavioral finance theory proposes an alternative opinion on market performance, because inefficiency of the market allows receiving additional revenues (Lo, 2004; Shiller, 2003).

Performance-wise, Sharpe (1991) demonstrates that actively managed portfolios must, on average, underperform the market benchmark after costs. The reasoning is straightforward: since active investors as a whole hold the same assets as the market, they must earn the same gross return as the market before fees. Once management fees and transaction costs are deducted, their net return must therefore fall below the market return. This issue prompts one to pose a question regarding the value of active management itself, which sets the context for the discussion of technical vs. fundamental analysis approaches in the present thesis.

2.2 Fundamental analysis

The term “fundamental analysis” means the technique used to establish the intrinsic value of a stock, using the economics of a business. According to Damodaran (2012), the intrinsic value of an asset can be defined as the present value of its future cash flow. This means that when fundamental analysis is applied in stock valuation, the variables considered include revenue, profits, cash flow and profitability ratios such as Price to Earnings Ratio (P/E) and Return On Equity (ROE). Fundamental analysis will be conducted in the current study based on certain screening criteria, which include positive ROE, low P/E ratio, debt/equity less than 1.5 and positive earnings growth as recommended by Fama & French (1992) and Damodaran (2012) in stock valuation using the value investment approach.

Empirical evidence to support this approach was provided right from the start of the research process. Ball and Brown (1968) provide proof that stock prices react positively to changes in earnings. This is important because it supports the idea that there is value-relevant information in the reports and accounting numbers matter. Not only changes in earnings but also changes

in other factors like inventory levels, accounts receivable, and gross margins can contribute to explaining stock return beyond the earnings factor. Their findings reinforce the use of multi-criteria screening in fundamental analysis, as they show that combining several financial indicators produces more reliable valuation signals than relying on a single metric. This supports the multi-criteria approach adopted in this thesis.

The importance of fundamental analysis is directly related to the discussion of market efficiency. According to Fama (1970), the stock price in an efficient market reflects all information known about the company; thus, investors cannot have any advantage in identifying misvalued stocks. The theory mentioned above is challenged by behavioral finance. The role of psychological influences and sentiment in pricing is recognized by Shiller (2003), while Barberis et al. (1998) emphasize cognitive biases in stock evaluation. Thus, in some situations, markets may be considered inefficient, giving reasons to rely on fundamental analysis.

However, the application of fundamental analysis faces several constraints. According to Malkiel (1995), equity mutual funds do not outperform market indexes after deducting expenses, and according to Carhart (1997), fund returns are mostly determined by their exposures to shared risk elements such as size and value instead of good stock selection. This indicates that although fundamental analysis offers an adequate conceptual basis for spotting undervalued stocks, its practical implementation is difficult.

2.3 Technical analysis

Technical analysis is a technique used in analyzing financial instruments, with a particular emphasis on understanding past price trends and volumes to uncover patterns and make decisions about buying or selling. Unlike fundamental analysis, which tries to establish the real value of a stock, technical analysis assumes that all necessary information, including human behaviors and psychology, is captured within the price trend itself, thus making it possible to predict future price trends (Brock et al., 1992).

Theoretically, technical analysis is a direct attack on the weak form of the Efficient Market Hypothesis (Fama, 1970). The Weak Form assumes that historical data cannot be used to forecast future performance. Behavioral finance provides an alternative foundation for understanding why technical strategies may work. According to Barberis et al. (1998), the presence of psychological biases causes over- and underreaction to news by investors, thus resulting in the formation of momentum and reversal phenomena among others. Shiller (2003) provides similar views regarding the effects of investor sentiment swings on market prices, supporting thereby the theoretical foundations provided in the preceding part.

Perhaps the most important study concerning technical analysis is the paper by Brock et al. (1992), which proves the effectiveness of such elementary strategies as crossover of moving averages. Lo et al. (2000) develop this idea by formulating a systematic approach to technical pattern recognition and demonstrating the information content of several such patterns.

Price indicators such as those suggested by Treynor & Ferguson (1985) may also be useful to gauge certain elements of market sentiment that cannot be gauged based on fundamentals alone. Moving average crossover signals, as studied by Brock et al. (1992), and the RSI indicator (Wilder, 1978) serve as the two analytical tools employed in this study.

But the effectiveness of technical strategies is not assured throughout the investment horizon. According to Lo (2004), as more and more traders use the same strategies, their profits become increasingly difficult to achieve, forcing them to make new adaptations. Since the implementation of technical strategies involves trading quite often, such strategies can be quite vulnerable to trading costs, as was pointed out earlier. The evidence provided by Jegadeesh & Titman (1993) regarding the presence of substantial momentum effects in stock returns shows that price movements contain valuable information, but also indicates that such trends reverse themselves eventually.

Finally, Zhu & Sun (2018) suggest that combining technical indicators with fundamental signals may enhance predictive power, pointing toward a hybrid approach that draws on the strengths of both methodologies, a perspective that is directly relevant to the comparison conducted in this thesis.

3. Literature review

3.1 Market efficiency as a theoretical baseline

Without a basic understanding of the theoretical background set out in the form of Efficient Market Hypothesis (EMH), the conflict between the two analyses, fundamental and technical, cannot be adequately assessed. Fama's (1970) review of both theoretical and empirical studies on market behavior describes market efficiency as a state in which "asset prices incorporate all relevant information". Three kinds of efficiencies are distinguished. The weak form states that existing prices include all previous prices, meaning that there is no use for technical analysis because no strategy can make extra profit from price history. The semi-strong form means that prices reflect all available public information (financial statements, economic statistics etc.) making fundamental analysis also unnecessary. Finally, the strong form suggests that all private information is also included in prices. However, this theory is rather exaggerated.

In light of this theoretical framework, there are far-reaching consequences for both of the approaches being compared in this thesis. In the case that the markets are weak-form efficient, the moving average crossover signals and the RSI indicators employed by the technical approach will not be able to create an edge. If the market is semi-strong efficient, then the fundamental approach will also fail. The EMH therefore provides the null hypothesis against which the results of this thesis are implicitly tested.

Fama & French (2010) revisit this debate in a more recent and comprehensive study, examining the performance of a large sample of US actively managed equity funds over the period 1984 to 2006. Using a bootstrap simulation methodology, they find that the distribution of fund alphas is consistent with what would be expected if no manager possessed genuine stock-picking skill. Very few mutual funds achieve statistically significant alpha, and this number is not higher than expected from random chance. They provide compelling evidence for the semi-strong form of the EMH, indicating that the combination of stock picking and market timing does not produce consistent excess returns, especially after deducting trading costs and management fees. However, Fama & French also note that at the extreme ends of the alpha distribution, a small number of managers do appear to generate consistent positive net alphas, suggesting that some genuine skill may exist. The critical question, however, is whether such managers can be identified *ex ante* rather than only in hindsight, which remains an open and unresolved issue in the literature. This result forms an important point of reference for the

current research since it brings up the possibility of breaking through this fundamental limitation.

Nevertheless, there have been many criticisms of the EMH from various perspectives since its emergence. According to Shiller (2003), the development of the efficient market hypothesis and the behavioral approach to finance argues that the assumption of rational investors systematically underestimates the role of psychological factors in driving asset prices. Extreme cases of irrational volatility have been observed in the financial markets which cannot be explained with respect to the phenomenon of efficient information within the market, such as the case of dot-com bubble in the late 1990s. Furthermore, Barberis et al. (1998) present a model that describes investor sentiment in which the psychological phenomena of conservatism and representativeness result in underreaction and overreaction to new information, causing predictable return patterns.

According to Lo (2004), Adaptive Markets Hypothesis (AMH) serves as an integrative approach that explains how the EMH fits in with behavioral finance anomalies. Instead of assuming that efficiency in markets is a static state that exists or does not exist, Lo asserts that it changes with the changing behaviors of market participants over time. Under the AMH, the profitability of any given strategy depends on the competitive landscape and the prevailing market regime. A strategy that generates alpha in one period may become ineffective as more investors adopt it, driving away the associated profits. However, an unsuccessful strategy in one market regime may yield positive results when the context changes. Such an approach is especially important to consider for the five-year timeframe explored in this thesis (2021→2025) where we observe a number of market regimes: pandemic-induced crash, fast recovery due to monetary policy adjustments, high inflation rates, and rising interest rates.

3.2 Evidence on fundamental analysis

The empirical foundations of fundamental analysis were established by Ball & Brown (1968) in one of the most influential early studies in accounting-based finance. Analyzing a sample of US firms over the period 1957 to 1965, they demonstrate that annual earnings announcements contain significant information content, as evidenced by the fact that stock prices begin moving in the direction of the earnings surprise several months before the official announcement date. The results obtained support the relevance of accounting information as they prove that there are signals in the information disclosed in financial statements which have not been captured by the stock market yet, and investors who analyze such information thoroughly can achieve an informational edge. The above result thus serves as a solid rationale behind the selection of earnings-related factors to be used in portfolio selection, and therefore supports the use of ROE and earnings growth as screeners.

Lev & Thiagarajan (1993) continue by highlighting other financial signals, apart from earnings per se, which are claimed to have significant use when valuing securities. By applying their model using Wall Street Journal, Barron's, and Value Line to determine the fundamentals used by practitioners, they analyze a total of 12 signals, among others, such as inventory, receivables, capital spending, and gross profit margin. Their empirical results indicate that out of the 12 variables used, most of them had incremental explanatory value when compared to earnings per se.

Moreover, their study results reveal that the importance of those signals is much higher if the interpretation takes place under the prism of the macroeconomic environment. It means that the fundamental analysis technique proves its effectiveness when several levels of information are

analyzed at the same time. The proposed multi-criteria analysis model based on the use of such criteria as P/E ratio, ROE, debt/ equity ratio, and earnings growth confirms this conclusion.

Fama & French (1992) introduce yet another perspective to the empirical investigation of fundamental analysis by pointing out that two basic accounting variables, namely firm size and book-to-market equity ratio, play a substantial role in explaining the cross-sectional variation of mean stock returns on NYSE, AMEX, and NASDAQ during the period 1963 to 1990. As per their study, stocks having a high book-to-market ratio, which suggests low P/E ratio and thus indicates financial distress or underestimation of the market, generate substantially higher mean returns than growth stocks. The value effect they found out was strong through sub-periods and could not be explained solely by market beta. Hence, it either indicates risk compensation or market misvaluation, which fundamental analysis can capitalize on. Indeed, their study offers explicit validation of the thesis's screening criteria that involve choosing value stocks whose P/E ratio ranks at the lowest 30%-40% range among those of the S&P 500 firms.

However, the application of fundamental analysis in practice is constrained by several factors. According to Malkiel's (1995) seminal study on the performance of U.S. equity mutual funds between 1971 and 1991, the average fund fails to outperform its benchmark index even after adjusting for transaction costs, and the underperformance becomes greater with extended holding periods because selecting mispriced stocks is challenging in light of competition. This finding is further supported by Carhart's (1997) work, where he introduces an additional momentum factor into the Fama and French three-factor model. Carhart shows that nearly all of the persistence in mutual fund returns can be attributed to exposure to risk factors, namely market risk, size, value, and momentum, and not to the skill of stock picking by fund managers. It is implied that any persistent excess returns attributed to stock selection skills are just systematic risk exposure that could be obtained at lower cost through a passive approach. Fama & French (2010) make similar findings using bootstrapping methods, which suggest that only a very small number of fund managers produce positive alpha, and that on average the alpha produced by active management is not statistically different from zero, meaning there is no true stock picking skill.

3.3 Evidence on technical analysis

One of the major advances made in establishing the scientific credibility of technical analysis is represented by the work conducted by Brock et al. (1992), which still constitutes the most often-cited empirical research in this area. Applying a set of basic technical trading rules (such as moving average crossover and trading range breakout strategies) on daily close prices of the Dow Jones Industrial Average for almost 90 years, from 1897 to 1986, they demonstrate that these rules result in abnormal profits. More specifically, it was found that buy trades based on moving average strategies lead to daily returns that exceed the unconditional mean by an average of 0.042%, while sell trades yield returns of 0.025% below the mean. The spread between buy and sell signals is significant for all the strategies and sub-periods tested, which provides ample proof that the hypothesis of the weak form of the EMH is not valid. Moreover, in order to overcome data-snooping bias, the authors perform bootstrap simulation, but again the results are found to be very robust. This research paper has special significance for our current thesis since the MA50/MA100 crossover signal in the technical trading strategy can be traced back to Brock et al.'s study of moving average strategies.

Lo et al. (2000) take this idea a step further by formally modeling the process of technical analysis through non-parametric kernel regression. In this paper, using daily stock prices for many companies within the US for the period 1962-1996, they objectively identify 15 common

patterns such as head-and-shoulders patterns, double top/bottoms, and triangle formations without any form of human subjectivity. A few of these patterns are seen to hold considerable value in terms of predicting the conditional distribution of returns in the future, especially when dealing with stocks that trade on the Nasdaq stock exchange. This paper is important not just because of the empirical evidence, but because of the approach used in this paper to formally incorporate technical pattern analysis into science through non-parametric kernel regression.

The work of Jegadeesh & Titman (1993) is an important complementary validation to the information embedded in the historical price through their research on momentum trading. Through their examination of the monthly return for all stock traded in the NYSE and AMEX between the years 1965 to 1989, the authors showed that the practice of buying outperformers and selling short losers in the preceding 3 to 12 months period earns substantial gains within the succeeding 3 to 12 months period. The monthly return generated from this momentum trading strategy varies from 0.93% to 1.49% based on how they choose to form and hold their investments, and such gains cannot be attributed to their exposure to the Fama-French risk factors. This momentum effect is directly relevant to technical analysis because moving average signals and RSI indicators are designed precisely to capture price trends and momentum, the persistence of price movements that Jegadeesh & Titman document. Nevertheless, it is important to note that there is usually a profit reversal tendency over periods ranging from two to five years, such that past winners perform worse than past losers. This brings into limelight one of the weaknesses of using trend-based techniques and emphasizes the necessity of having a correct timing mechanism.

A more theoretical justification for technical analysis is provided by Treynor & Ferguson (1985). According to them, the difference between fundamental and technical information is not as obvious as it may seem at first glance. The authors state that movements in prices contain information on the expectations of all people on the market, even those who possess better-quality information than others, and that there is sufficient information for an experienced technical analyst in price trends to interpret. In this way, technical analysis may be regarded as a process of information aggregation, which is close to the concepts developed by behavioral finance.

Nevertheless, the profitability of technical methods does not always remain constant since it is known to degrade over time. According to Lo (2004) under the theory of adaptive markets, when more and more people become aware of such rules and use them, then profits will become zero due to the disappearance of arbitrage opportunities in such markets. The same may explain why it was easier for Brock et al. (1992) to achieve abnormal returns using pre-1986 data compared to what this research considers. Transaction costs represent a further and significant constraint. Since technical strategies typically involve more frequent rebalancing than buy-and-hold approaches, they are particularly exposed to execution costs such as bid-ask spreads and brokerage commissions, which Sharpe (1991) shows must in aggregate erode the net returns of any active strategy below those of a passive benchmark.

More recently, Han et al. (2021) offer a broad overview of academic research on technical analysis, including traditional technical indicators as well as more recent techniques using machine learning algorithms. Their study indicates that technical indicators maintain significant prediction accuracy for stock returns in different financial markets over various time periods, and that machine learning algorithms, such as Lasso regressions, neural nets, and genetic programming, have managed to boost the ability of price patterns to predict future stock returns. Thus, in addition to the traditional technical analysis tools being useful to forecast stock market

returns, machine learning has proven effective, which goes against Lo's (2004) suggestion that technical indicators will cease to yield valuable information due to high competition.

This broader trend of applying machine learning to investment strategies extends beyond technical analysis alone. DeMiguel et al. (2023) show that machine learning methods, particularly gradient boosting and random forests, can exploit fund characteristics to construct portfolios of mutual funds that generate statistically significant out-of-sample annual alpha of 2.4% net of all costs. However, their findings reveal that, although there is some genuine management ability among active funds, the ability to detect such skills can only be achieved using advanced predictive techniques capable of detecting nonlinear relationships between funds' features and their future performance, something which cannot be accomplished using traditional methods. Moreover, it should be noted that past performance is found to be especially strong predictor of future performance among actively traded funds, and that machine learning is capable of detecting management ability that allows active managers to succeed despite all the difficulties involved in trading larger funds. In sum, the findings of this study cast doubt upon the idea of EMH's semi-strong form and indicate that the ability to beat markets hinges more on the detection rather than existence of investment skill.

3.4 Toward a hybrid approach

A growing body of literature suggests that combining fundamental and technical analysis produces better results than either approach applied in isolation, and that the two methodologies may be more complementary than competing. One of the empirical studies that test this hypothesis is conducted by Bettman et al. (2009). In their paper, they develop a valuation model of stocks based on both the fundamental and technical indicators using data from Australian-listed firms. They conclude that even though each type of indicator is individually effective in explaining stock prices, when used together in an integrated model, they can explain prices more effectively. They conclude that fundamental and technical analysis should be viewed as complements rather than substitutes, with each capturing a different dimension of the information set available to investors. This finding directly motivates the parallel design of the present thesis, which applies both approaches to the same portfolio universe and explicitly compares their respective contributions to performance.

The authors Zhu & Sun (2018) take the above discussion one step further by suggesting a combination model for investing that uses both fundamental and technical indicators, which is described as being based on the long-term value philosophy of Warren Buffett, combined with technical signals from Bollinger Bands. When tested on US stocks, this strategy proves more profitable than either the pure fundamental or pure technical strategies. Their results suggest a clear division of roles between the two methodologies: fundamental criteria are effective at identifying which securities to hold over the long run, while technical signals help improve the timing of entries and exits. This division of roles is directly reflected in the methodology of the present thesis, where the fundamental strategy determines the portfolio composition through annual screening, and the technical strategy modifies the timing of trades within that same universe of securities.

Treynor & Ferguson (1985) also support this view, noting that there is not one information source adequate enough to allow for optimal investment decisions. These authors suggest that the combination of various kinds of signals, including price-based and fundamental information, helps investors take advantage of a larger number of inefficiencies present in the market. This approach is further supported by the findings in behavioral finance, suggesting that markets can be inefficient in multiple ways at once. Barberis et al. (1998) find that investors

both underreact and overreact to certain information, indicating that an investment strategy capable of responding to both kinds of market inefficiencies will outperform a strategy focused only on one.

The literature therefore converges on a nuanced picture. Fundamental analysis works well at spotting undervalued stocks over time periods, especially in markets where there is a value effect as found by Fama and French (1992). However, technical analysis is more useful for exploiting short-run momentum patterns as shown by Brock et al. (1992) and Jegadeesh and Titman (1993). In addition, neither technique works all the time, and depending on the state of the market, one would be more effective than the other, an assertion supported by the Adaptive Markets Hypothesis of Lo (2004).

4. Data used

4.1 Presentation of the data studied

The analysis in this thesis has been based on the financial history data available for the period from January 1, 2021 to December 31, 2025, making five consecutive years. This time frame has been selected because of the diversity of the regimes available in it, which makes it an ideal environment to compare the performance of fundamental versus technical approach, as suggested by the Adaptive Markets Hypothesis framework of Lo (2004).

The 2021 trend in equity markets showed an overall positive direction, which was a result of the monetary policies of expansion as well as the fiscal stimulus packages provided due to the pandemic of coronavirus. The favorable conditions for investing in stocks were provided due to low-interest rates and the recovery of earnings, as the S&P 500 grew by 30.84%. On the other hand, 2022 was marked by a dramatic shift in the investment environment due to the highest rate hike cycle in decades implemented by the Fed to address persistently high levels of inflation. Equity valuation multiples decreased significantly due to higher discount rates, leading to a decline in the S&P 500 index by 18.65%. 2023 was an excellent year for the market as it witnessed the recovery of the market with the participation of a few firms in the technology sector whose market value was very high owing to the theme of artificial intelligence. This resulted in the index gains of 26.71% although the participation of the broad market was quite limited. The year 2024 was that of normalisation in which the Fed began to reduce interest rates as inflation levels started falling below its 2% target, thereby facilitating a gain of 26.05%. Finally, 2025 saw some economic uncertainty due to geopolitical conflicts and trade policies leading to returns of 18.89%.

The series of different market regimes from monetary easing to tight monetary policy, recovery through technological innovation, normalisation and then uncertainty once again, make the period 2021-2025 a suitable period to undertake the comparative analysis of investment strategy because both types of investment will be exposed to a wide range of market conditions.

Investment universe consists of stocks included in the S&P 500 Index, which is an index composed of the 500 largest companies listed on US stock exchanges, sorted according to their market capitalization. There are several reasons for the choice of the S&P 500 Index as a basis of this research. First, the S&P 500 Index is probably the most widely investigated equity index among those considered in the academic literature; therefore, the results obtained in this research can be directly compared with other studies, e.g., Brock et al. (1992), Fama & French

(1992) and Jegadeesh & Titman (1993). Secondly, the universe includes enough stocks meeting the basic requirements. Finally, data on the S&P 500 Index are easily available.

In this study, there are two main sources of data that will be used. Firstly, adjusted close prices of all stocks in the S&P 500 index will be gathered on a daily basis throughout the whole period of the study. Adjusted prices take into account dividend payments as well as stock splits; thus, the returns calculated using such prices will reflect the total return of the investor, which includes dividends. Such an approach is in line with the methodology employed in the works of Fama & French (1992) and Jegadeesh & Titman (1993), both using total return data in their empirical studies. Price data will be collected from Yahoo Finance using yfinance Python library. Secondly, fundamental data such as P/E ratio, ROE, Debt/Equity ratio, EPS, and Market Cap will be collected on an annual basis. Fundamental data will be gathered from Bloomberg Terminal as of January 1st of each portfolio year, reflecting trailing twelve months data available to the investor on this date. Bloomberg Terminal was chosen because of the high reliability and consistency of its data, which is widely used in academic and professional literature when studying S&P 500 constituents. It is consistent with the frequency of annual rebalancing used in this paper as described in section 4.3.

One important methodological consideration concerns the issue of look-ahead bias, defined as the erroneous use of information that would not have been available to the investor at the time of the investment decision (Pardo, 2008). In order to ensure that only information accessible to the investor at the time of portfolio construction was incorporated, the fundamental screening was conducted strictly on the basis of data available on Bloomberg as of January 1st of each portfolio year. For instance, the portfolio constructed on January 1st, 2022 relies exclusively on fundamental data available as of that date, corresponding to the most recently reported trailing twelve-month figures for each constituent of the S&P 500 index.

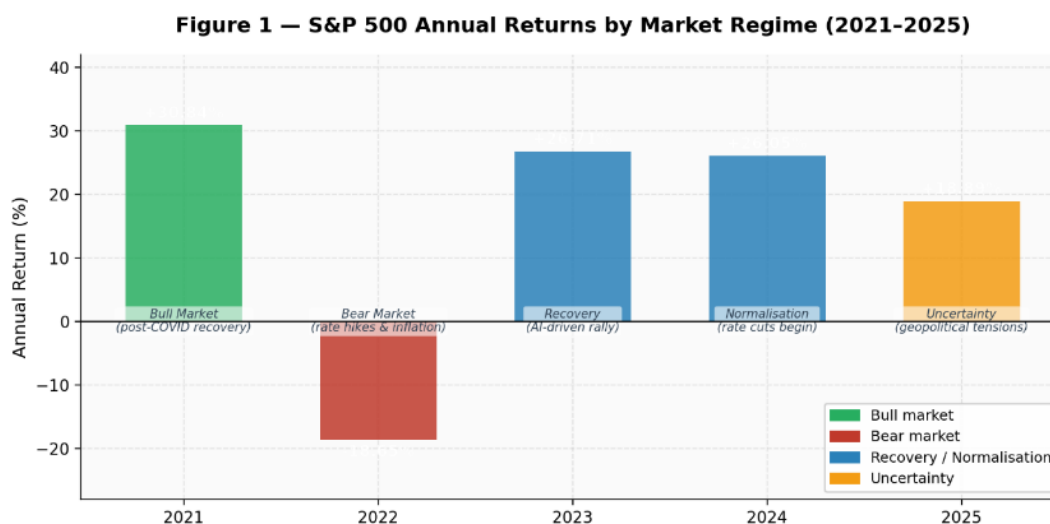


Figure 1 : S&P 500 Annual Returns by Market Regime (2021–2025).

The chart illustrates the five distinct market regimes covered by the study period: the post-COVID bull market of 2021 (+30.84%), the Fed-driven bear market of 2022 (−18.65%), the AI-led recovery of 2023 (+26.71%), the normalisation of 2024 (+26.05%), and the geopolitical uncertainty of 2025 (+18.89%).

Source: Yahoo Finance via yfinance and author's calculations.

4.2 Hypotheses

On the basis of the theoretical background laid out in the conceptual framework and the literature review, along with the empirical context established through the data in Section 4.1, the current study hypothesizes about three aspects. It is aimed to empirically examine the relative efficiency of the fundamental and technical approaches in analyzing the same portfolio of S&P 500 stocks during 2021-2025.

Hypothesis 1: Fundamental analysis generates superior risk-adjusted returns compared to technical analysis over the full study period.

The hypothesis is that the investment strategy on the value-screened portfolio of stocks, especially the buy-and-hold strategy, will produce better risk-adjusted performance than the technical strategy over the entire analysis period. This hypothesis is based on the value investing theories developed by Fama and French (1992), who proposed that stocks with lower P/E ratios have the potential to produce higher returns. In addition, the value investing theories presented in Damodaran's (2012) book on business valuation provide the basis for this hypothesis. The use of the multiple criteria stock screening technique, including ROE, P/E ratio, debt/equity ratio, and EPS growth rate, is expected to be able to select stocks that have higher intrinsic values than their market prices.

Part of the reasoning for why fundamental analysis ought to be superior stems from the results of Ball and Brown (1968) and Lev and Thiagarajan (1993) that prove that the fundamental indicators of finance possess information regarding the future performance of stocks that is not captured by market prices at once. On the other hand, technical analysis that employs moving average crossovers is vulnerable to the shortcomings of a trend-following strategy, namely, the lag in generating entry/exit signals, whipsaws in range-bound markets, and vulnerability to trading costs (Sharpe, 1991; Brock et al., 1992). Over a long period of time, the buy-and-hold approach will enable the investor to avoid such difficulties and compound their profits from good stocks without any losses.

Risk-adjusted performance is measured using the Sharpe ratio and the Sortino ratio, as detailed in Section 4.5. H1 is confirmed if the fundamental strategy generates a higher Sharpe ratio and Sortino ratio than the technical strategy over the 2021–2025 period as a whole.

Hypothesis 2: The relative performance of the two strategies varies significantly across market regimes.

The second hypothesis is that there is no single strategy that can be said to possess absolute supremacy over other strategies in all types of markets; on the contrary, the superiority of a particular strategy depends on the current market regime. The basis for this hypothesis is Lo's (2004) Adaptive Markets Hypothesis (AMH). The AMH suggests that the performance of any strategy is not constant; rather, it changes in response to the changing nature of competition and the general economic environment. As such, a strategy that succeeds in one regime could fail in another regime.

In this case, it is hypothesized that the buy-and-hold strategy will succeed when the market experiences bullish conditions where there are rising equity values, increasing corporate profits, and low interest rates because the strategy will be able to fully exploit the potential gains in equity price without the delay associated with moving averages. The year 2021 is expected to

favor the fundamental strategy because of the rally in equity markets due to expansive monetary policies.

On the other hand, the technical strategy will be expected to enjoy a comparative advantage during bear-market years characterized by falling stock prices, increasing interest rates, and worsening firm fundamentals. This will occur since the death cross will trigger early portfolio liquidations before the worst part of the market correction hits, thus protecting capital from further losses. 2022, a year characterized by the Federal Reserve's aggressive interest rate hikes and a general decline in the stock market, will be the time when the technical strategy's capital preservation features will shine through.

The forecast for 2023 recovery period is not entirely clear. While the fundamental strategy is likely to gain from holding appreciated securities for the entire year, the technical strategy will partly miss out on the early stages of the market rebound because of the inherent lag in the MA50 crossing over the MA100 following a bear market period. Even though the use of the MA100 as the long-term moving average (instead of the typical MA200) reduces the lag effect compared to slower crossover systems, the lag cannot be avoided after a prolonged market downtrend as it requires that the short-term moving average first stabilizes and then crosses over the long-term moving average. According to Brock et al. (1992), this lag effect for moving-average crossover strategies is likely to widen the return gap between the two strategies, especially during sharp market reversals, since the fundamental strategy of buying and holding stocks will benefit from capturing a bigger part of the recovery gain at the beginning.

If the results show significant differences in annual returns and Maximum Drawdown between the two strategies, and the fundamental strategy outperforms during bull-market years while the technical strategy performs better during bear-market years, then Hypothesis H2 will be accepted.

Hypothesis 3: Neither strategy generates economically significant alpha relative to the market benchmark.

The third hypothesis is that the fundamental and technical strategies do not generate risk-adjusted returns that are economically superior to the SPY passive benchmark, as measured by the Sharpe ratio and Sortino ratio, after controlling for market risk exposure. This hypothesis is based on the semi-strong form of the Efficient Market Hypothesis as formulated by Fama (1970) which states that security prices fully and instantaneously incorporate all publicly available information, making it impossible for any strategy based on publicly available data, whether fundamental financial statements or historical price patterns, to systematically generate risk-adjusted excess returns.

This hypothesis is supported empirically by Fama and French (2010), who, using bootstrap simulations, prove that the distribution of alphas among the large number of actively managed equity funds in the United States is indicative of the lack of stock picking ability on the part of any manager, and of only a tiny minority of funds having statistically significant alphas. Similarly, Malkiel (1995) and Carhart (1997) prove that persistence of mutual fund returns results from exposure to systematic risks, rather than from investment expertise. This hypothesis has its theoretical basis in Sharpe (1991), who argues that the aggregate effect of active management will be unable to outperform passive indexing after costs, because the aggregate portfolio of active managers will always be equal to the market portfolio.

For the technical strategy, an additional source of support for H3 comes from Lo (2004), who argues under the AMH that any alpha generated by technical trading rules tends to erode over time as more market participants adopt the same signals, driving away the associated profits. The declining profitability of moving average strategies in more recent sample periods relative to the historical evidence of Brock et al. (1992) is consistent with this prediction.

Conclusion: H3 will be validated if neither of the two strategies produces risk-adjusted excess returns that are economically significant relative to the SPY passive strategy benchmark in the 2021–2025 period, as evaluated using the Sharpe ratio and the Sortino ratio measures, and when the Sharpe ratio of both strategies is not significantly higher than the Sharpe ratio of the benchmark strategy. Inability to produce risk-adjusted returns higher than the SPY benchmark would suggest informational efficiency in the S&P 500 index.

4.3 Methodology

4.3.1 Universe and investment period

The investment universe is made up of stocks that belong to the S&P 500 Index as of January 1st of each portfolio formation year. Since S&P 500 stocks are highly liquid, stocks selected using the screening process will have prices that match those used during backtests and hence there will not be any effects on the market from such transactions.

Five portfolios will be formed each year from January 1st through December 31st over five consecutive years (2021 through 2025). The frequency of annual portfolio formation is in line with the common practice of reviewing fund managers' portfolio investments on an annual basis based on the new financial statements provided by firms (Damodaran, 2012).

4.3.2 Screening procedure

Each year, on the first day of January, a rule-driven screening approach is adopted for the purpose of selecting the top 20 attractive investments from among the S&P 500 investment universe. This process incorporates the concepts of value investment, which have been discussed by Damodaran (2012), along with the empirical evidence provided by Fama and French (1992), who have shown that fundamental ratios could predict asset returns. The criteria used for selecting such assets include six conditions, each of which must be analyzed prior to the following one.

The first criterion filters out all companies that have negative Return on Equity ($ROE < 0\%$). In other words, for a firm to qualify under this criterion, it has to exhibit a positive return on its equity (Ball & Brown, 1968; Damodaran, 2012). Second, the criteria exclude all firms whose price-earnings ratio is above the 40th percentile, considering the idea behind value investing that favors stocks that are relatively undervalued as compared to other stocks (Fama & French, 1992). Third, the leverage criterion excludes all firms that have a Debt/Equity ratio of more than 150%. The fourth criterion requires positive year-over-year earnings growth, formally defined as $EPS\ Growth = \frac{(EPS_t - EPS_{t-1})}{EPS_{t-1}} > 0$. An EPS-based measure is preferred over a net income-based one, as it accounts for variations in share count, thereby providing a more stable and accurate reflection of per-share profitability improvement (Ball & Brown, 1968; Lev & Thiagarajan, 1993). The fifth criterion retains only companies reporting a positive current EPS (Damodaran, 2012). Finally, the sixth criterion excludes firms whose market capitalisation falls

outside the 10th to 90th percentile range of the eligible universe, thereby removing both the largest mega-cap constituents and the smallest-cap securities (Fama & French, 1992).

The P/E and market capitalisation thresholds are recomputed annually on the basis of the eligible universe, defined as securities exhibiting complete data, a positive P/E ratio, and a positive EPS. This dynamic recalibration ensures that the selection criteria adapt to prevailing market conditions rather than being fixed with an arbitrary selection. From the securities satisfying all six criteria, the 20 companies displaying the lowest Price-to-Earnings ratios are selected. An equal-weighting scheme is then applied across all 20 constituents, consistent with the approaches advocated by Jegadeesh and Titman (1993) and DeMiguel et al. (2023).

4.3.3 Portfolio construction and rebalancing

The portfolio is reconstructed annually on January 1st based on fundamental data as of that date, reflecting the typical investment horizon of a fundamental equity fund manager (Damodaran, 2012). Each security receives an initial allocation of \$50 at the start of each portfolio year, yielding a total initial portfolio value of \$1,000. Stocks removed from the S&P 500 during the year are retained until December 31st, consistent with the annual rebalancing rule. This introduces a minor survivorship bias, acknowledged as a limitation in Chapter 6.

4.3.4 Two strategies

Both strategies are applied to exactly the same portfolio of 20 stocks selected through the screening procedure described above. The only difference between them lies in how each strategy manages entry and exit from individual positions during the year.

The fundamental strategy implements a pure buy-and-hold approach. All 20 selected securities get bought at the opening price on January 2nd and then kept until December 31st, even if the price keeps moving all year. This kind of method matches the longer horizon idea in fundamental analysis, where people look at intrinsic value instead of the daily, or even short-lived, price noise (Damodaran, 2012; Bettman et al., 2009).

The technical approach applies a Moving Average crossover rule to the same 20 securities to govern entry and exit decisions throughout the year. This approach builds on the framework introduced by Brock et al. (1992) and subsequently formalised by Lo et al. (2000). In particular, a long position is initiated when the MA50 crosses above the MA100 (Golden Cross). The position is closed when the MA50 crosses below the MA100 (Death Cross). Entry and exit decisions are determined exclusively by this crossover signal.

Relative Strength Index (RSI, 14-period, according to Wilder, 1978) is not utilized as a trading signal in this paper, but it can be viewed as a supplemental measure to interpret the momentum conditions under which each trade entry took place. In particular, the RSI value at the moment when each Golden Cross trading signal occurs reveals more details about the momentum environment: A trade entry executed when RSI was low means that there is more upside momentum ahead as the stock has not been fully overbought yet; conversely, if RSI is high at the time when Golden Cross occurs, it is unlikely that the security will generate much momentum anymore.

A reason why MA50/MA100 is preferred over the more traditional MA50/MA200 crossover lies in the ability of the former to react quicker to changes in trends. The first reason behind the choice is that the use of a short window results in less lag compared to other crossovers. The

quicker reaction makes it possible to identify changes in the trend and therefore miss fewer upturns after a downtrend. Another advantage of the MA100 over the shorter-moving average MA50 is that the former filters short-term market movements to minimize trading mistakes in the sideways price movements.

In addition, there are three other operational rules that apply to implementing the technical approach strategy. The first rule states that positions will never be taken in situations where the MA50 line has yet to cross above the MA100 line at the onset of the year, in which case the allocation for that stock will remain in cash until a Golden Cross occurs. The second rule involves keeping invested capital in cash if a Death Cross does not occur, or if there are no holdings at the onset of the year, because zero-cost opportunity is assumed. The third rule states that any positions left open on the last day of the year should be sold at the close of trading on that day. These positions would be forced to liquidate by the end of the year in order to prepare for portfolio rebalancing.

4.4 Data processing

4.4.1 Fundamental data

Fundamental data, like the Price-to-Earnings ratio, the Return on Equity, Debt-to-Equity ratio, Earnings Per Share, and Market Capitalisation were retrieved from the Bloomberg Terminal as of January 1st for each portfolio year. These were trailing twelve-month figures that an investor could see at that moment. Using point in time data from Bloomberg also makes sure that any forward looking does not contaminate the screening process.

EPS-based earnings growth was computed by merging each year's Bloomberg export with the prior year's EPS figures. Where Bloomberg reported Net Income as unavailable (primarily for financial sector companies with non-standard accounting structures) the EPS-based growth metric remained computable, reducing the proportion of missing data from approximately 38–43% under a Net Income approach to below 5% under the EPS approach.

4.4.2 Price data

Daily adjusted closing prices for all portfolio securities were obtained from Yahoo Finance via the yfinance Python library, covering the period from June 2020 to December 2025. Adjusted prices account for stock splits and dividend distributions, ensuring comparability across the full sample period. For the technical strategy, the MA100 is calculated using 100 calendar days of price data prior to the start of each portfolio year, ensuring its full availability from January 1st onwards. All signals are computed on a rolling basis using only data available up to and including the previous trading day, preserving the integrity of the backtest.

4.4.3 Exclusion rules and data cleaning

Several decisions about data processing were taken in order to maintain consistency in methodology. The stocks which joined the S&P 500 list in the previous calendar year were not included in the analysis because they had no complete historical information in relation to EPS and, thus, would have triggered the need to employ look-ahead bias in order to compute earnings growth as an inclusion criterion (Pardo, 2008). Companies having Class A shares, as more liquid securities, had only one ticker each: Fox Corporation (FOX/FOXA), Alphabet (GOOG/GOOGL), and News Corp (NWS/NWSA). There were also some Bloomberg tickers identified using special numeric symbols like 9991429D for Aptiv and 9990213D for Jacobs

Solutions; they were considered continuing assets rather than newly added securities. Lastly, five Yahoo tickers that were not available as they were deleted after the sampling period was closed (PARA, DFS, and DISH in 2022, and MRO and PXD in 2023) were substituted for the next ticker in the ranking list – HOLX, HPE, and TSN in 2022, and TFC and QCOM in 2023.

4.4.4 Missing data

Stocks for which Bloomberg Terminal could not provide complete data across all fundamental criteria are excluded from the screening universe prior to the application of the screening filters. This exclusion is applied consistently across all five portfolio years and is consistent with standard practice in the empirical asset pricing literature (Fama & French, 1992).

4.5 Performance measurement

For every portfolio year and for every strategy, performance time-series of stocks are aggregated into a portfolio time-series, which is defined as the sum of portfolio value on a given day across the 20 stocks. The daily portfolio return is calculated as the percentage change in the total portfolio value from one day to the other. This aggregate portfolio time-series serves as the starting point in calculating all risk measures for portfolios such as annualized volatility, Sharpe ratio, Sortino ratio and Maximum Drawdown. On the other hand, average annual return and the hit rate for portfolios are calculated as equally weighted average of the cross-section of individual stock returns. The risk-free rate is set at 2% per annum throughout the study, converted to a daily equivalent as $\frac{R_f}{252}$ where required.

4.5.1 Annual return

The primary performance measure is the average annual return of the portfolio, defined as the equally-weighted cross-sectional average of the individual stock returns over the calendar year:

$$R_{portfolio} = \frac{1}{N} \sum_{i=1}^N R_i$$

where $N = 20$ and R_i is the annual return of security i under the relevant strategy. Under the fundamental strategy, R_i corresponds to the buy-and-hold return from January 2nd to December 31st. Under the technical strategy, R_i reflects the cumulative return generated by the MA50/MA100 crossover rule applied to security i over the year, including periods of cash holding during which no return is earned.

4.5.2 Annualised volatility

Annualised volatility is computed as the standard deviation of daily portfolio returns, scaled by the square root of 252 trading days:

$$\sigma_{annual} = \sigma(R_{daily}) \times \sqrt{252}$$

where $R_{daily} = \{r_1, r_2, \dots, r_T\}$ is the time series of daily returns of the aggregated portfolio over the measurement period, and $\sigma(R_{daily})$ denotes the standard deviation of that series. Volatility represents the overall spread in returns around the mean return of the portfolio and forms the denominator in the Sharpe ratio. For a given average return, a lower volatility signifies a more

efficient portfolio. It is expected that the technical approach will show a lower volatility compared to the fundamental approach owing to the fact that it incorporates some amount of cash holdings while the position is idle since a day where there is no investment produces an absolute zero in return.

4.5.3 Sharpe ratio

The Sharpe ratio, first proposed by Sharpe (1966) and subsequently employed extensively in performance evaluation studies (Carhart, 1997; Fama & French, 2010), is defined as follows:

$$\text{Sharpe ratio} = \left[\frac{\bar{R}_{daily} - \frac{R_f}{252}}{\sigma(R_{daily})} \right] \times \sqrt{252}$$

where $\bar{R}_{daily}$ is the mean daily return of the aggregated portfolio, R_f is the annual risk-free rate of 2%, and $\sigma(R_{daily})$ represents the daily standard deviation of portfolio returns. While normally, a Sharpe ratio that is above 1 is considered satisfactory, one that is above 2 indicates exceptional performance; however, such criteria cannot be accepted as fixed standards as the suitable Sharpe ratio varies with the kind of asset, situation, and time period. As regards this particular case, the Sharpe ratio that we would consider is the one derived from the portfolio returns for the whole period rather than the average Sharpe ratio of the 20 stocks.

4.5.4 Sortino ratio

The Sortino ratio improves upon the Sharpe ratio in that it penalises for downside volatility alone, which is daily returns less than the daily risk-free rate, instead of total volatility (Sortino & van der Meer, 1991):

$$\text{Sortino ratio} = \left[\frac{\bar{R}_{daily} - \frac{R_f}{252}}{\sigma(R_{daily}^-)} \right] \times \sqrt{252}$$

where $\bar{R}_{daily}$ is the mean daily return of the aggregated portfolio, R_f is the annual risk-free rate of 2%, and $\sigma(R_{daily}^-)$ is the standard deviation of daily portfolio returns that are strictly below the daily risk-free rate $\frac{R_f}{252}$.

Sortino ratio can be especially helpful when evaluating the two strategies discussed in this paper due to their distinctive features. The technical strategy tends to hold cash under adverse circumstances, meaning that the returns generated by the technical strategy have an inherently asymmetric distribution, which is very different from the returns generated by the fundamentally oriented strategy, which invests all of its funds at all times. When not making any investments, the technical strategy neither makes nor loses money, but at the same time lowers its downside volatility compared to the other strategy.

4.5.5 Maximum drawdown

Maximum Drawdown (MDD) measures the largest peak-to-trough decline in the aggregated portfolio value over the measurement period:

$$MDD = \min_t \left[\frac{V_t - \max_{s \leq t}(Vs)}{\max_{s \leq t}(Vs)} \right] \times 100$$

where V_t is the total portfolio value at time t , obtained by summing the individual stock portfolio values across all 20 securities. The maximum drawdown represents the worst-case experience an investor will have by investing in the portfolio from the highest point until reaching the lowest point after that, which is a crucial measure of risk and ability to preserve capital (Damodaran, 2012). While the volatility considers upside and downside equally, the maximum drawdown only considers the downside experience, and thus it is more helpful in assessing the protective nature of the strategy when the market is bearish.

4.5.6 Hit ratio

The hit ratio is defined as the proportion of portfolio securities generating a positive annual return in a given year:

$$Hit\ ratio = \frac{\sum_{i=1}^N \mathbf{1}(R_i > 0)}{N} \times 100$$

where $N = 20$. By capturing the range of positive contributions across the 20 securities, regardless of their amount, this statistic offers a complementary viewpoint on portfolio performance. When evaluating the stability and consistency of each strategy's stock selection and timing choices, a high hit ratio shows that portfolio performance is widely dispersed among securities rather than being driven by a few outliers.

4.5.7 Exposure ratio

Given the distinctive nature of the technical strategy, which alternates between invested and cash positions throughout the year, an additional metric, the Exposure ratio, is computed to capture the average proportion of trading days during which each security holds a long position:

$$Exposure\ ratio = \frac{1}{N} \sum_{i=1}^N \frac{D_i}{T} \times 100$$

This metric has no equivalent for the fundamental strategy, which maintains full market exposure throughout the year. When the ratio is smaller, the implication is that the technique is able to generate its profit without a lot of exposure to the market, thus contributing to the lower volatility and maximum drawdown compared to the fundamental technique. This means that the Exposure ratio becomes important information when measuring the risk-reward relationship of the technical technique. Additionally, the ability of the technique to generate profits is automatically limited when there is a small exposure ratio during the bull market year.

4.5.8 Transaction cost sensitivity

As the number of trades is considerably higher for the technical approach compared to the fundamental approach, a sensitivity test is carried out to evaluate how trade commissions will affect the outcome of the technical approach. The three commission rates used are 0.1%, 0.25%, and 0.5%. The net annual return under each scenario is computed as:

$$R_{net} = R_{gross} - (\bar{k} \times c)$$

where $\bar{k}$ represents the average number of round-trip transactions per stock per year and c represents the rate of commissions per transaction in percentages, the opposite is the case for the underlying approach, which requires a mere one round-trip transaction per stock per year. This analysis directly addresses the theoretical argument of Sharpe (1991) that active trading strategies face a structural cost disadvantage relative to passive approaches, and provides a practically relevant assessment of the viability of the technical strategy in a real-world implementation context.

4.5.9 Distributional metrics: Skewness and Kurtosis

Two higher-order distributional metrics are computed on the cross-sectional distribution of individual stock returns within each portfolio year, providing additional insight into the shape and tail behaviour of the return distributions generated by each strategy.

Asymmetry in the distribution of return can be determined using skewness. In case the skewness is positive, a few positive outliers make the returns higher than the mean for many stocks while negative skewness will indicate the opposite. Excess kurtosis indicates the degree to which the tail is heavy relative to the tail in normal distribution. Positive excess kurtosis indicates heavier tails. A negative excess kurtosis indicates a distribution with thinner tails. These metrics are particularly important when comparing the technical and fundamental strategies because the cash holding periods present in the technical strategy are expected to compress the distribution of the returns towards zero in terms of lower dispersion and perhaps even different skewness characteristics than the fully invested fundamental approach.

4.5.10 Statistical significance testing

For every portfolio year, a Welch's t-test is performed to determine whether the observed differences in average yearly returns between the technical and fundamental strategies are statistically significant or due to sample variance. Given the structurally distinct return distributions of the two techniques, Welch's t-test is favored above the conventional Student's t-test since it does not assume equal variances across the two samples (Welch, 1947). The test statistic is computed as:

$$t = \frac{\mu_T - \mu_F}{\sqrt{\frac{S_T^2 + S_F^2}{n}}}$$

where μ_T and μ_F are the mean returns of the technical and fundamental strategies respectively, S_T^2 and S_F^2 are their sample variances, and $n = 20$ is the number of securities. For this study, a p-value of less than 0.05 represents the criterion of statistical significance. These findings are presented with the other findings in Chapter 5 and form the foundation for concluding on the relative performances of the two strategies.

4.5.11 Benchmark comparison

A comparative analysis of the performance of both techniques has been carried out based on three benchmarks from the market. First among these is the SPDR S&P 500 ETF Trust (SPY) as the ETF itself follows the S&P 500 Index and will be representative of the return earned by a passive investor in the period. Two other benchmarks considered for the comparison are iShares Russell 1000 Value ETF (IWD) and iShares Russell 1000 Growth ETF (IWF). Here the IWD can serve as a benchmark due to its likeness to the technique used for stock selection, just

like the technique followed by a passive investment instrument such as value. Considering the dominance of growth stocks in the years 2023 and 2024 due to the boom in technology during these years from which the two methods evolved, IWF serves as the appropriate benchmark.

5. Results

This chapter presents the empirical results of the backtest conducted over the period 2021–2025. Section 5.1 examines the performance of the fundamental strategy, Section 5.2 addresses the technical approach, and Section 5.3 provides a comparative analysis of both strategies against the benchmark indices. All performance metrics are computed in accordance with the methodology outlined in Section 4.5.

5.1 Performance of the fundamental strategy

5.1.1 Annual returns

The fundamental strategy generated positive returns in four out of five years, with an average annual return of 11.24% over the 2021–2025 period. Table 1 summarises the annual performance of the strategy alongside the SPY benchmark.

Table 1 : Fundamental Strategy: Annual Returns vs SPY Benchmark (2021–2025)

Year	Fund. Return	SPY	vs SPY (pp)	Hit Ratio	Market Regime
2021	+33.56%	+30.84%	+2.72%	95%	Bull Market
2022	−13.06%	−18.65%	+5.59%	20%	Bear Market
2023	+12.42%	+26.71%	−14.29%	55%	Bull Market
2024	+14.34%	+26.05%	−11.71%	75%	Bull Market
2025	+8.92%	+18.89%	−9.97%	75%	Bull Market
Average	+11.24%	+16.77%	−5.53%	64%	—

Source: Bloomberg Terminal (fundamental screening data), Yahoo Finance via yfinance (price data) and author's calculations. Hit ratio represents the proportion of portfolio securities generating a positive return in the given year.

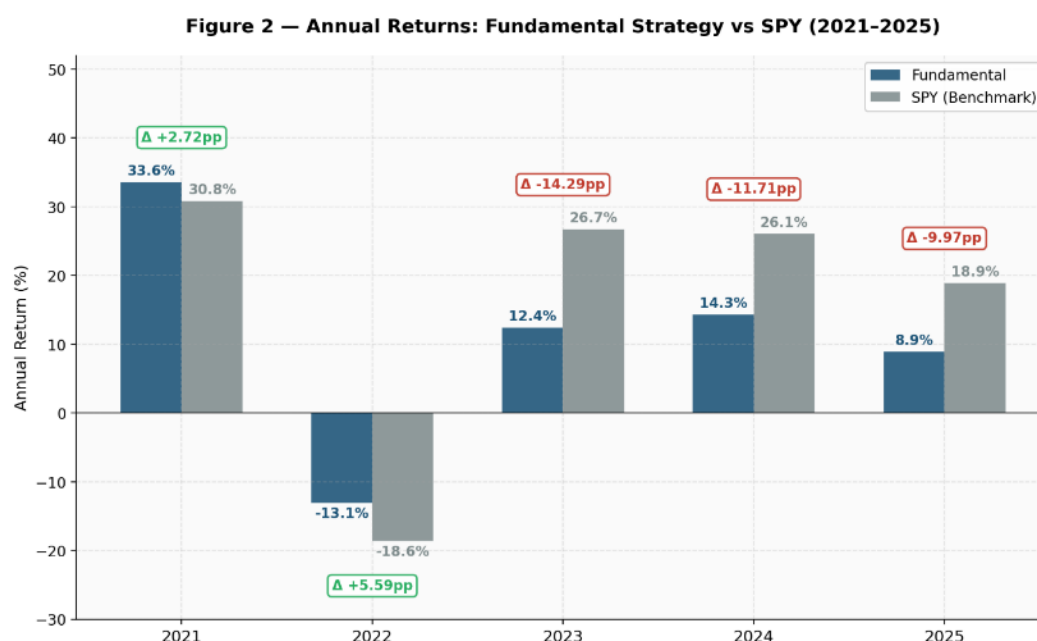


Figure 2 : Annual Performance: Basic Strategy Compared to SPY Benchmark (2021-2025). The blue bars depict the buy-and-hold strategy based on the fundamentals approach while the grey bars depict the SPY returns. The Δ marks highlight the performance difference for each year in percentage points. The basic strategy outperformed the SPY benchmark in 2021 (2.72%) and 2022 (5.59%), but underperformed during 2023

Source: Bloomberg Terminal; Yahoo Finance via yfinance; author's calculations.

The best performing year for the strategy was 2021, when it outperformed the SPY by 2.72% to register a return of 33.56%. The results in 2021, in conformity with the findings of Fama and French (1992), can be attributed to the value nature of the screening criteria used, such as low P/E ratios, positive growth in earnings, and modest debt levels, due to the rally in the equity markets and rotation towards value in the same year. Contributions from individual stocks were spread wide and the 95% hit rate indicated that the superior performance did not result from isolated anomalies but instead, from a generalized rise.

The basic approach turned out to be quite durable during the bear market of 2022, when it resulted in only a 13.06% decline versus the SPY's drop of 18.65%, a relative outperformance of 5.59%. In addition, due to the low-P/E nature of the screened stocks, there was some valuation protection against the general de-rating of the stock multiples driven by the Fed rate hikes, which can be explained by the defensive character of value stocks during bear markets as noted by Fama and French (1992). While the overall loss remained much smaller compared to the benchmark, the hit ratio fell to 20% in 2022.

The basic strategy underperformed the SPY stock by 14.29%, 11.71% and 9.97% for the years 2023, 2024 and 2025 correspondingly. However, the composition of the screen portfolio is dominated by finance, insurance, house builders and energy companies which are expected to underperform as far as the technology stock rally in 2023 and 2024 is concerned, which was a dominant factor in the composition of S&P 500 stock price index. Underperformance of fundamental strategy is consistent with growth to value divergence during this period when large tech stocks were responsible for much of the index increase and other value-driven stock markets made relatively smaller contributions. In any case, underperformance does not mean that the screening technique failed since the basic strategy produced positive absolute returns for three out of five years of analysis period.

5.1.2 Risk profile

Table 2 : Fundamental Strategy: Annual Risk Metrics (2021–2025)

Year	Volatility	Sharpe Ratio	Sortino Ratio	Max Drawdown	Market Regime
2021	14.72%	1.92	2.88	-7.19%	Bull Market
2022	26.94%	-0.46	-0.75	-29.04%	Bear Market
2023	18.14%	0.63	1.12	-18.51%	Bull Market
2024	15.69%	0.81	1.38	-11.45%	Bull Market
2025	17.91%	0.46	0.63	-14.11%	Bull Market
Average	18.68%	0.67	1.05	-16.06%	—

Source: Author's calculations based on daily adjusted close prices from Yahoo Finance. Volatility = annualised standard deviation of daily portfolio returns. Sharpe ratio computed using the 3-month US Treasury bill rate as the risk-free rate. Sortino ratio uses downside deviation (below zero) as the denominator. Maximum drawdown = largest peak-to-trough decline over the calendar year.

Figure 3 — Fundamental Strategy: Annual Risk Profile (2021-2025)

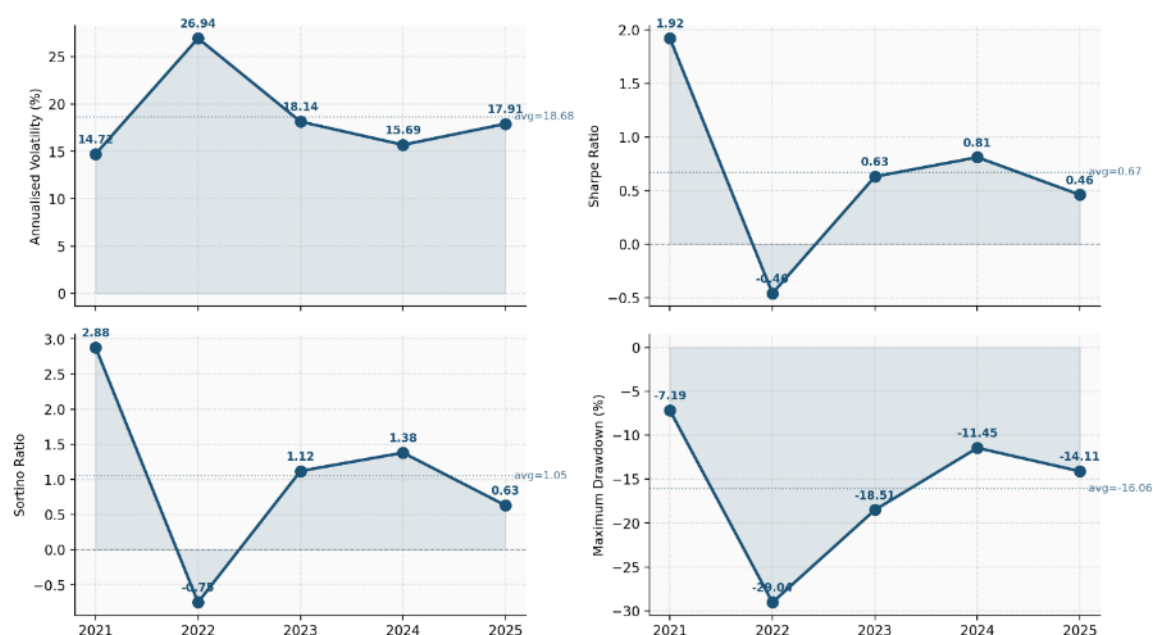


Figure 3: Risk Profile for Each Year (2021–2025). The following four charts demonstrate annual volatility, Sharpe ratio, Sortino ratio, and maximum drawdown per year. Dashed line indicates the average for five years according to each of these parameters. Shaded area indicates how far away each parameter is from its average value.

Source: Author's calculations based on Yahoo Finance daily price data.

However, the fundamental strategy showed an average annualised portfolio volatility rate of 18.68% for the year as a whole, considering the full market risk position kept during the entire year. The average Sharpe ratio of 0.67 implies acceptable risk-adjusted returns, but the variations in annual returns were high from 1.92 in 2021 to -0.46 in 2022. The average Sortino ratio of 1.05 confirms that the strategy provides sufficient compensation for downside risk over the entire period. The average Maximum Drawdown of -16.06% indicates the strategy's susceptibility to individual stocks' drawdowns during the adverse market phases. The worst

drawdown occurred in 2022 at -29.04% , when the broad-based decline in equity valuations caused simultaneous losses across most of the portfolio holdings.

5.1.3 Hit ratio

The hit ratio came to an average of 64% for the entire five-year timeframe, the highest being in 2021, where there was a 95% hit ratio while the lowest came in 2022 with a hit ratio of 20%. This significant disparity suggests that the overall performance of the fundamental strategy is very highly correlated with general market performance since a rise in the market will result in gains across most stocks in the portfolio while a fall in the market will lead to losses among most holdings.

5.1.4 Statistical significance

The results of Welch's t-test for the significance of the mean returns of each individual stock by comparing the fundamental and technical strategies show statistically significant differences for the year 2021 ($t = -2.23$, $p = 0.032$), as well as for the year 2023 ($t = -2.22$, $p = 0.034$), favoring the fundamental strategy. The difference in mean returns in 2022, 2024 and 2025 years is not statistically significant at the 5% significance level.

Table 3 : Welch's t-Test Results: Statistical Significance of Return Differences between Fundamental and Technical Strategies (2021–2025).

Year	t-statistic	p-value	Significant at 5%?	Better Strategy	Interpretation
2021	-2.23	0.032	Yes ✓	Fundamental	Fund. significantly outperforms in bull market (+11.48pp gap)
2022	n.s.	>0.05	No	—	No statistically significant difference despite absolute gap
2023	-2.22	0.034	Yes ✓	Fundamental	Fund. significantly outperforms during recovery (+16.20pp gap)
2024	n.s.	>0.05	No	—	Performance gap not statistically distinguishable from sampling variation
2025	n.s.	>0.05	No	—	Performance gap not statistically distinguishable from sampling variation

Ho: There is no statistically significant difference between the means of the individual stock returns for both strategies for any year. The use of Welch's t-test (Unequal variances assumed) on the cross-section of individual stock returns ($n=20$ for each strategy every year). N.S. = Not Significant at 5%.

Source: Author's calculations.

5.2 Performance of the technical strategy

5.2.1 Annual returns

Over the period 2021-2025, the technical strategy was profitable in three out of five years, posting an average annual return of 5.33%, far below the fundamental strategy, but with much less market exposure. The annual performance is summarized in Table 4.

Table 4 : Technical Strategy (MA50/MA100 Crossover): Annual Returns vs SPY Benchmark (2021–2025)

Year	Tech. Return	SPY	vs SPY (pp)	Exposure Ratio	Avg. Trades / Stock	Market Regime
2021	+22.08%	+30.84%	-8.76%	74.30%	4.2	Bull Market
2022	-9.82%	-18.65%	+8.83%	35.76%	4.3	Bear Market
2023	-3.78%	+26.71%	-30.49%	49.36%	4.1	Bull Market
2024	+12.98%	+26.05%	-13.07%	77.37%	3.5	Bull Market
2025	+5.21%	+18.89%	-13.68%	53.13%	4.1	Bull Market
Average	+5.33%	+16.57%	-11.24%	58.00%	4.0	—

Source: Author's calculations based on daily adjusted close prices from Yahoo Finance.

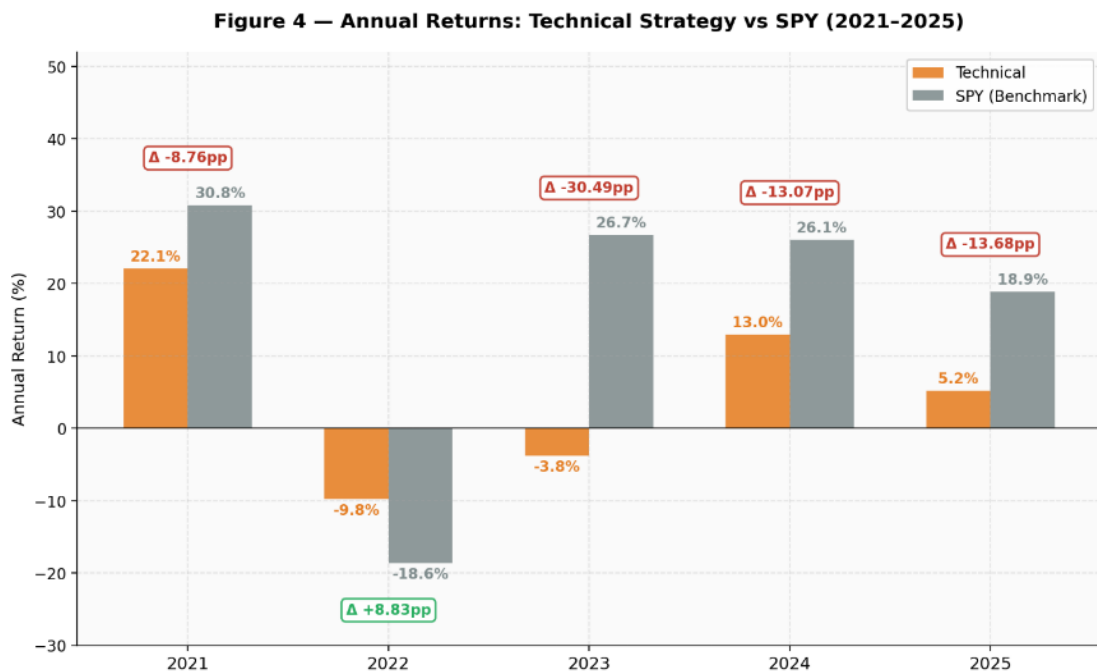


Figure 4 : Annual Returns: Technical Strategy vs SPY Benchmark (2021–2025). Orange bars represent the MA50/MA100 crossover portfolio, grey bars represent the SPY. Δ labels indicate annual outperformance or underperformance in percentage points. The technical strategy only outperformed the SPY in 2022 (+8.83pp) and it underperformed most sharply in 2023 (−30.49pp) due to the delayed Golden Cross signal after the market trough.

Source: Bloomberg Terminal, Yahoo Finance via yfinance and author's calculations.

One specific characteristic of the technical approach is its asymmetric performance in various market conditions. For instance, in 2022, which was a bad year for the SPY since its fall reached

19.65 percent, the technical strategy performed much better with only 9.82 percent lost and, therefore, was better than the benchmark by 883 bps. The fact that the strategy performs defensively can be explained by its very principle of operation based on the MA50/MA100 cross, which means that with the negative performance of the assets, numerous death crosses were triggered, forcing investors to get rid of them and wait with money in hands.

The technical strategy yielded a positive return of 22.08% in 2021, being an example of good absolute performance despite falling behind the fundamental strategy and SPY by 11.48 and 8.76 percentage points, respectively. This difference results from the cost associated with the technical approach used in the strategy, which leads to temporarily exiting the market amid temporary corrections in security prices.

The technical strategy was a major underperformer in 2023, returning -3.78% compared to SPY's gain of 26.71% and the fundamental strategy's 12.42% return. This difference is well known in the lagging nature of moving-average-based strategies. After the late 2022 market bottom, the MA50 took several months to cross above the MA100, leaving the strategy in cash for a large part of the early rally of the recovery. Although the use of the MA100 rather than the more conventional MA200 reduces this lag, the reversal in 2023 was sufficiently sharp to leave the strategy significantly behind the buy-and-hold approach. This result is consistent with the findings of Brock et al. (1992), who acknowledge that moving average strategies structurally underperform during sharp market reversals.

5.2.2 Risk profile

Table 5 : Technical Strategy (MA50/MA100 Crossover): Annual Risk Metrics (2021–2025)

Year	Volatility	Sharpe Ratio	Sortino Ratio	Max Drawdown	Exposure Ratio	Market Regime
2021	11.72%	1.60	2.31	-6.78%	74.30%	Bull Market
2022	10.59%	-1.12	-1.61	-15.94%	35.76%	Bear Market
2023	9.97%	-0.54	-0.80	-13.87%	49.36%	Bull Market
2024	12.95%	0.86	1.41	-9.36%	77.37%	Bull Market
2025	9.58%	0.38	0.51	-7.33%	53.13%	Bull Market
Average	10.96%	0.24	0.36	-10.66%	58.00%	—

Source: Author's calculations based on daily adjusted close prices from Yahoo Finance. All metrics defined as in Table 2, Exposure ratio = proportion of trading days with active equity positions, as determined by MA50/MA100 Golden Cross (entry) and Death Cross (exit) signals.

Figure 5 — Technical Strategy: Annual Risk Profile (2021-2025)

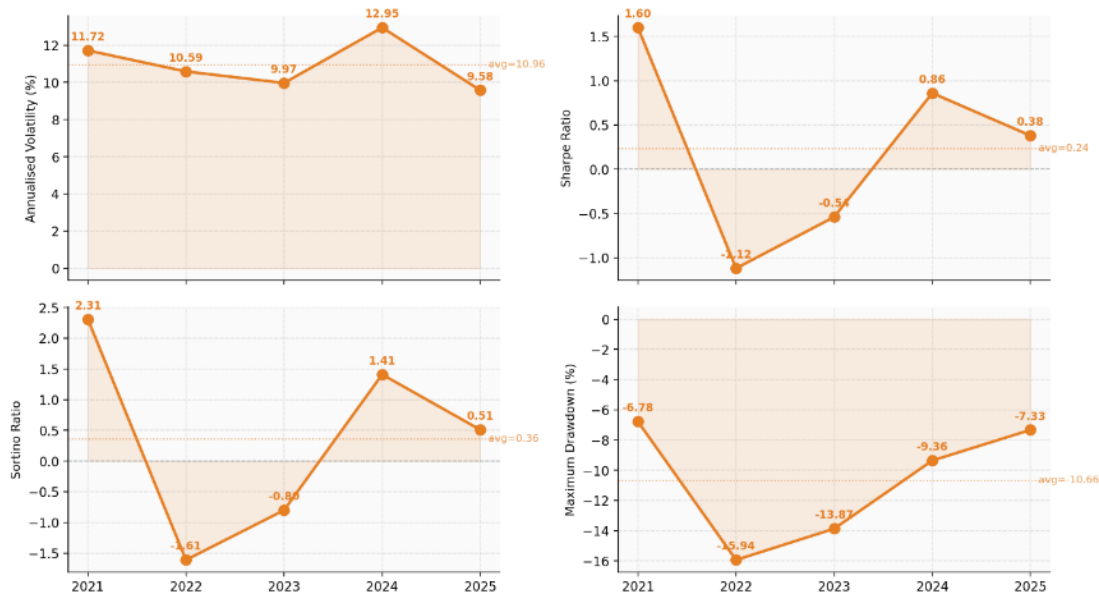


Figure 5 : Technical Strategy: Annual Risk Profile (2021–2025). The four panels display annualised portfolio volatility, Sharpe ratio, Sortino ratio, and maximum drawdown for each year. The technical strategy maintained structurally lower volatility (avg. 10.96%) across all years due to its partial cash-holding mechanism. Dotted lines indicate the five-year average.

Source: Author's calculations based on Yahoo Finance daily price data.

The technical strategy had a structurally smaller portfolio volatility in comparison to the fundamental strategy, on average 10.96% annually versus 18.68% annually in case of fundamental strategy – a decrease by about 41%. Such structural difference in volatility is caused by the partial cash involvement into the trading strategy. In the case of the formation of Death Cross, money involved in position formation are no more exposed to daily return volatility, and it consequently leads to the smaller dispersion of portfolio returns. An average Sharpe ratio is substantially lower in case of technical strategy – 0.24 versus 0.67 for the fundamental strategy. It means that return decreased more in comparison to volatility. An average Sortino ratio, similar to Sharpe ratio, is also smaller and equal to 0.36 in case of technical strategy versus 0.67 in case of fundamental strategy. An average Maximum Drawdown for technical strategy is equal to -10.66% and is significantly smaller than one in case of fundamental strategy – -16.06%.

5.2.3 Exposure ratio and transaction activity

Figure 6 — Technical Strategy: Market Exposure Ratio by Year (2021–2025)

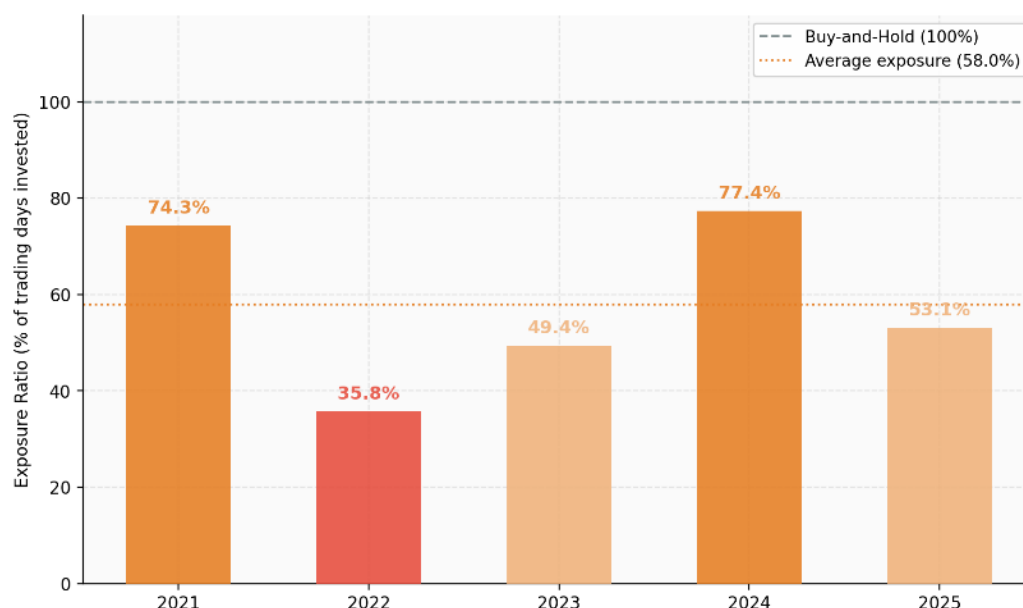


Figure 6 : Technical Strategy: Market Exposure Ratio by Year (2021–2025). Bars represent the proportion of trading days with active equity positions, as determined by MA50/MA100 Golden Cross (entry) and Death Cross (exit) signals. The dashed line marks 100% buy-and-hold exposure, the dotted line marks the five-year average of 58.0%. In 2022 the strategy was invested for only 35.76% of trading days.

Source: Author's calculations.

The exposure ratio ranged from 35.76% in 2022, the year of bear market, to 77.37% in 2024, indicating that the market participation of the strategy varies significantly across market regimes and is directly sensitive to the prevailing trend condition. The average long holding period in the full period was about 58% of trading days, the rest (42%) was cash.

The average number of trades per security per year was 4.0 round-trips, compared to a single round-trip for the fundamental strategy. With transaction cost of 0.1%, the annual net return from the technical analysis approach is lower by around 0.4%; with transaction cost of 0.25%, the annual net return is lower by around 1%; and with transaction cost of 0.5%, the annual net return is lower by around 2%. Such reductions become significant in light of the average gross return of the technical approach, which stands at 5.33%, as well as increase the performance lag between the technical and fundamental approaches under consideration.

5.3 Comparison and analysis

5.3.1 Overall performance comparison

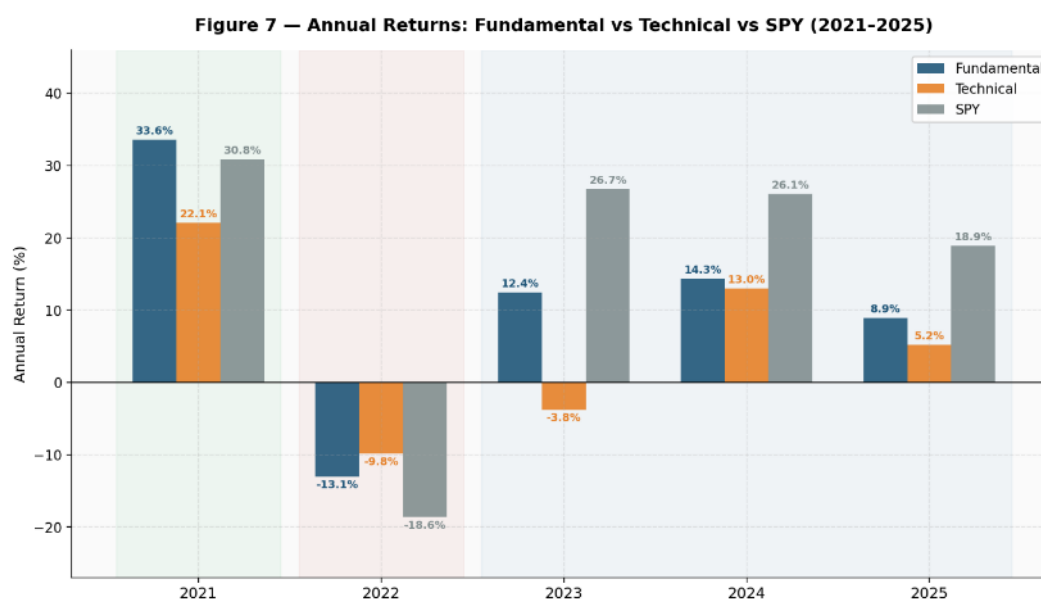


Figure 7 : Annual Returns: Fundamental Strategy vs Technical Strategy vs SPY Benchmark (2021–2025). Blue: fundamental buy-and-hold. Orange: MA50/MA100 technical. Grey: SPY passive benchmark. Background shading indicates market regimes (green: bull; red: bear; blue: recovery/normalisation/uncertainty). The fundamental strategy outperformed the technical strategy in absolute return in four out of five years.

Source: Bloomberg Terminal, Yahoo Finance via yfinance and author's calculations.

Table 6 : Consolidated Performance Summary: Fundamental vs Technical vs Benchmarks (2021–2025 Averages).

Metric	Fundamental	Technical	SPY	IWD (Value)	IWF (Growth)
Avg. Annual Return	+11.24%	+5.33%	+16.57%	+12.05%	+19.93%
Avg. Portfolio Volatility	18.68%	10.96%	—	—	—
Avg. Sharpe Ratio	0.67	0.24	—	—	—
Avg. Sortino Ratio	1.05	0.36	—	—	—
Avg. Max Drawdown	-16.06%	-10.66%	—	—	—
Avg. Hit Ratio	64%	56%	—	—	—
Avg. Exposure Ratio	100%	58.00%	—	—	—

Green (Fundamental) / Red (Technical) = which active strategy performs better on each metric. For volatility, maximum drawdown and exposure ratio, a lower value is preferable (technical wins).

Source: Bloomberg Terminal, Yahoo Finance (IWD, IWF total returns), author's calculations. SPY = SPDR S&P 500 ETF Trust. IWD = iShares Russell 1000 Value ETF. IWF = iShares Russell 1000 Growth ETF. '—' = metric not computed for benchmark indices.

Both methods underperform the SPY index relative to the average annual rate of return throughout the sample period, in accordance with the theory proposed by Sharpe (1991) and empirical results shown by Fama and French (2010). In regard to risk-adjusted performance,

the fundamental approach performs superior to the technical one as measured by average return (11.24% compared to 5.33%), Sharpe ratio (0.67 compared to 0.24), and Sortino ratio (1.05 compared to 0.36). Meanwhile, the technical approach exhibits a substantially smaller value of Maximum Drawdown (-10.66% compared to -16.06%) and portfolio volatility (10.96% compared to 18.68%).

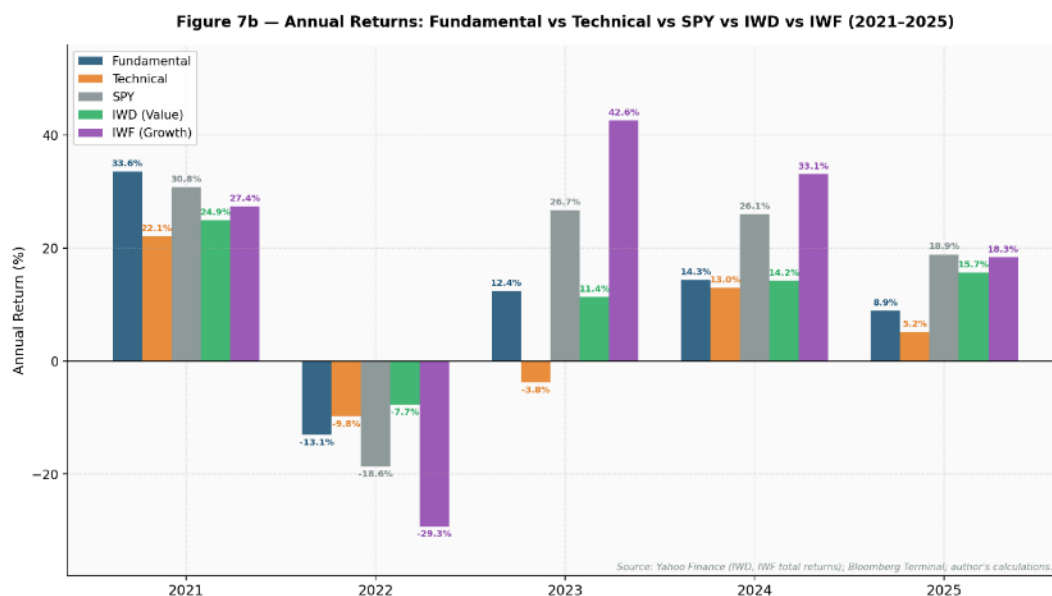


Figure 7b : Annual Returns: Fundamental vs Technical vs SPY vs IWD (Value) vs IWF (Growth) (2021–2025). IWD and IWF act as benchmarks for their respective styles. The profile of returns for the base strategy approach is very similar to that of IWD, thus reaffirming the value factor orientation of this approach.

Source: Bloomberg Terminal, Yahoo Finance via *yfinance* and author's calculations.

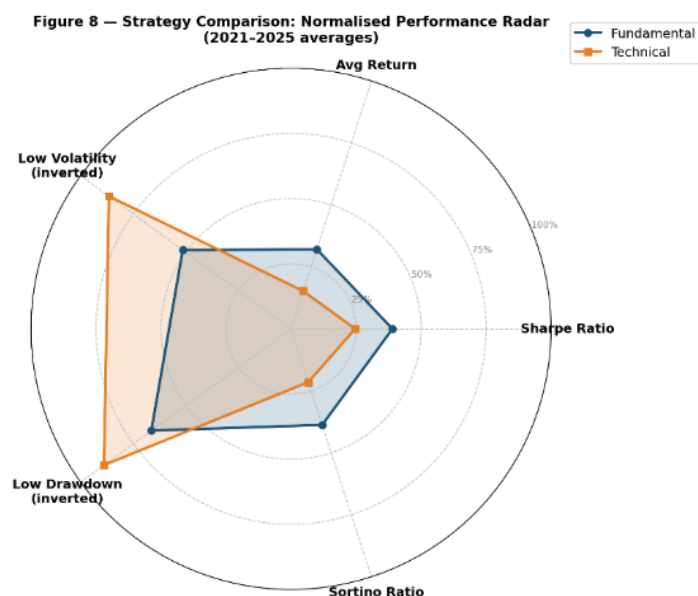


Figure 8 : Performance Radar Normalised: Fundamental Strategy vs Technical Strategy (average 2021–2025). Each axis is normalised to between 0 and 100%, where larger numbers indicate better performance, for drawdown and volatility axes, larger numbers mean worse performance. Blue shows dominance in terms of return generating strategies; orange shows capital preservation..

Source: Author's calculations based on five-year averages in Tables 2, 5, and 6.

5.3.2 Hypotheses testing

Hypothesis 1: Fundamental analysis generates superior risk-adjusted returns:

These results provide strong evidence in favor of H1. The fundamental beats the technical approach in all risk-adjusted performance indicators such as annualized returns (+11.24% vs. +5.33%), Sharpe ratio (0.67 vs. 0.24), and Sortino ratio (1.05 vs. 0.36). The results from the application of the Welch's t-test show that the superior performance by the former approach was significant in two out of five years: 2021 ($p = 0.032$) and 2023 ($p = 0.034$), which happened to be precisely the two years when the bull market environment benefited the buy-and-hold method more than others. H1 is thus supported with the limitation that the technical approach had an upper hand on drawdown avoidance and volatility reduction.

Hypothesis 2: Performance varies across market regimes:

The results strongly support H2. In the bear market year 2022, the technical strategy outperforms the fundamental strategy in terms of absolute return (−9.82% vs −13.06%) and Maximum Drawdown (−15.94% vs −29.04%). The technical strategy sells positions after Death Cross signals and stays in cash during the strongest phases of the market decline. On the other hand, the basic strategy beats the diversified one in the four bullish years, 2021, 2023, 2024, and 2025; in particular, the returns are 33.56% compared to 22.08%, 12.42% against −3.78%, 14.34% against 12.98%, and 8.92% against 5.21%. The fact that there are regimes under which a certain strategy beats another strategy is indeed what the Adaptive Markets Hypothesis proposed by Lo (2004). The exposure ratios data supports this interpretation. The technical strategy was deployed only 35.76% of the time in 2022, confirming that its outperformance that year was due mainly to capital preservation rather than stock picking.

Hypothesis 3: Neither strategy generates significant alpha:

The results are largely consistent with H3. For the full period, returns for both strategies are below the SPY benchmark, and neither strategy generates enough outperformance to be attributed to true stock-picking or market-timing skill, as opposed to market exposure or sampling variation. The fundamental strategy outperforms its market risk level slightly, consistent with the mild value premium in its screening criteria (Fama & French, 1992). The technical strategy underperforms its risk-adjusted expectation slightly, consistent with the declining profitability of trend following rules in increasingly competitive markets (Lo, 2004). Both results are not economically significant and are consistent with H3. Both results are in line with the broader conclusion of Fama and French (2010) that active investment strategies do not systematically produce excess returns over the market after risk adjustment.

5.3.3 Return distribution

The return distribution analysis reveals structurally different patterns between the two strategies across the five years of the study, as illustrated in Figures 9 and 10.

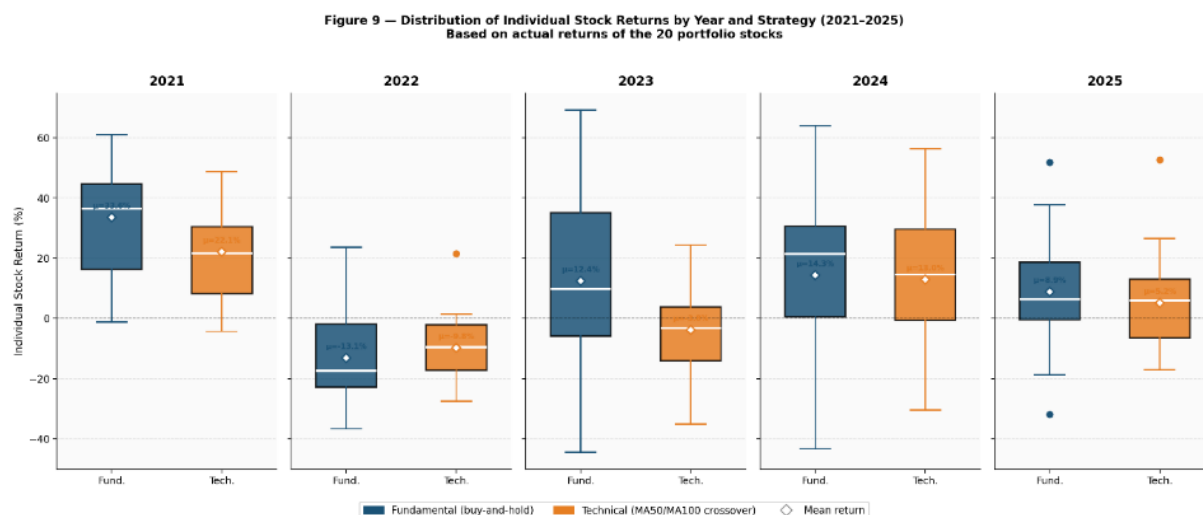


Figure 9: Distribution of Individual Stock Returns by Year and Strategy (2021–2025). Each panel shows the distribution of the 20 individual stock returns for a given year. The box spans the range where the middle 50% of stocks landed, the white line inside is the median return and the white diamond is the mean (μ). The vertical lines (whiskers) extend to the most extreme non-outlier stocks, dots beyond the whiskers are individual stocks with unusually high or low returns. Blue = fundamental buy-and-hold strategy; orange = MA50/MA100 technical strategy applied to the same 20 securities. The technical strategy produces a consistently more compressed distribution due to cash-holding periods.

Source: author's calculations based on actual portfolio stock returns (2021–2025).

The distributions in 2021 can be seen as widely spread out and relatively symmetrical, due to the overall bull market trend that created gains in most securities. The distribution for the basic strategy is slightly negatively skewed (-0.36) since there were a few underperformers that brought down the left side, whereas most of the values fall within the $+15\%$ to $+55\%$ gain. The technical distribution is almost completely symmetrical (-0.03).

In 2022, the distributions significantly move toward the left for both strategies due to the negative returns that were earned from these strategies in the bear market. Nonetheless, despite the prevalence of negative returns, the two distributions are still positively skewed. This paradox can be attributed to the few extremely positive values of the stocks in each distribution, for instance, the GILD stock had a positive fundamental return of 23.68% and a positive technical return of 21.55% , while NUE recorded a positive fundamental return of 18.54% . Another factor contributing to this distribution pattern is the concentration of the technical distribution near zero since there were many days when the portfolio was in cash position due to lack of profitable trades.

The difference between the two strategies is most clearly visible in 2023 when the distribution for the fundamental strategy has a wide spread, going from a minimum return of -44.44% (MRNA) to a maximum of $+69.15\%$ (DHI), compared to the technical strategy's tight distribution that has most of its returns within the range of -35% to $+25\%$. The latter result has to do with the delayed signals of the Golden Cross during the recovery period after the bear market bottom of 2022.

Figure 10 — Return Distribution: Density Curves (KDE) by Year and Strategy (2021-2025)
Curve height reflects the concentration of stocks at each return level

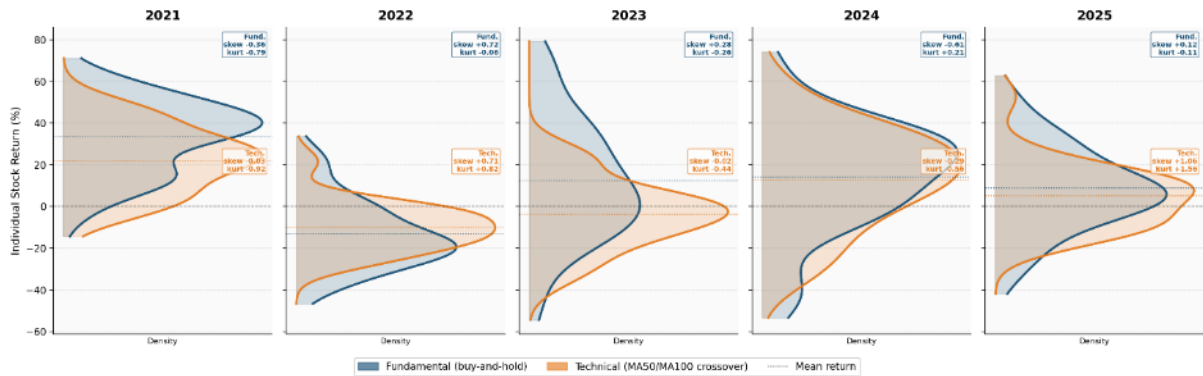


Figure 10 : Distribution of Returns: Density Curves (KDE) per Year and Strategy (2021-2025). This graph presents the kernel density estimation of individual stock returns within a specific year. A broader and higher density curve indicates a higher number of stocks at that particular return value. Blue line represents the fundamental buy and hold strategy while the orange line indicates MA50/MA100 technical analysis on the same 20 stocks. Dashed lines denote the average return per strategy. Skewness denotes asymmetry of the data distribution (positive values indicate tail is skewed towards profit, negative value indicate tail skewed towards losses). Excess Kurtosis denotes the degree of extreme returns beyond the normal expectation.

Source: author's calculations.

The density graphs shown in Figure 10 also help illustrate these structural disparities. The basic approach always yields broader and flatter graphs, which is a sign of increased variability and diversity in stock results. The technical strategy, by contrast, tends to generate narrower, more peaked distributions, particularly in years characterised by prolonged cash-holding periods such as 2022 and 2023. In 2024 and 2025, the two distributions converge notably, consistent with the higher exposure ratio of the technical strategy (77.37% and 53.13% respectively) and the more moderate market conditions of the normalisation and uncertainty regimes.

5.3.4 Transaction cost impact

The sensitivity analysis of transaction costs reveals the practical disadvantage of the technical strategy when considering real-world implementation. Assuming a commission of 0.25% per transaction, a realistic assumption for institutional trading, the average net annual return of the technical strategy is reduced to around 4.33%, increasing its underperformance versus the fundamental strategy to around 6.91 percentage points per year on average. At 0.5% per transaction, the difference widens to about 7.91 percentage points. The results are consistent with Sharpe (1991) who concluded that active trading strategies have a structural cost disadvantage, which is especially severe for high frequency trend following strategies relative to low-turnover buy-and-hold strategies.

6. Limitations and further research

6.1 Survivorship bias and data constraints

One important limitation of this study relates to survivorship bias and data availability constraints. Although the portfolio construction process relies on point-in-time Bloomberg data and annual S&P 500 constituents, several securities became unavailable on Yahoo Finance during the sample period due to mergers, acquisitions, ticker changes, or delistings. In such cases, the affected securities were replaced by the next qualifying company in the screener

ranking in order to preserve the portfolio size and ensure the continuity of the backtesting procedure.

These replacements have been conservatively made based on limited evidence, but there is still the potential for an upward bias in reporting portfolio returns. The reason why the stocks are missing from the public market is because of a history of bad performance or poor financial standing or even because the stock was acquired under such terms, and hence, excluding the data will generate an erroneous conclusion that the performance level of the portfolios is better than it actually is. Although this is a common issue in asset pricing studies involving historical index constituents (Fama & French, 1992), it remains an important methodological consideration that should not be overlooked.

The study also relies on adjusted price data from Yahoo Finance, which are publicly available. Yahoo Finance is broad in its coverage and sufficiently reliable for academic backtesting, but is not an institutional-grade database like CRSP or Compustat. Therefore, there may be minor differences regarding adjusted prices, dividend treatment, or historical ticker continuity. The use of Bloomberg Terminal improves the quality and consistency of accounting data for fundamental screening significantly, whereas the price component of the analysis is still partly dependent on publicly available sources.

6.2 Sample period limitations

Another limitation is the short-term nature of the analysis. The period under empirical scrutiny is the years 2021-2025, representing five portfolios per year and about 1,250 business days. Over this period, a variety of market regimes have occurred, such as post-pandemic economic recovery, hawkish central bank monetary policies, inflationary pressure, and geopolitical uncertainties. However, relative to financial market studies, this period represents an extremely short period of observation.

Thus, the short time frame under consideration makes it crucial to analyze the effect of such events on the results of this research. Especially, a sharp shift on the stock markets of 2022 and a technology-related boom in 2023 are essential when speaking about differences between the two strategies utilized in this research. According to the Adaptive Markets Hypothesis introduced by Lo in 2004, any investment strategy is valid only at a certain time depending on changes in market conditions and the investor's behavior. It means that findings acquired in this research might not be relevant in other cases when other economic conditions prevailed.

Using an extended time frame would improve the statistical validity of the findings, as well as allow for a deeper understanding of how sustainable the noted relationships have been. In actuality, the response that MA models exhibit through long-term secular periods of market trends might very well differ significantly from the cycles in 2021-2025.

6.3 Portfolio construction assumptions

The approach used to construct the portfolios in the research under analysis entails the use of various assumptions as well. For instance, all the portfolios will contain an equal weight since all stocks will be assigned the same weight regardless of their market value, liquidity, and riskiness. Despite the fact that equal weighting has proven highly popular within empirical finance studies (Jegadeesh & Titman, 1993; DeMiguel et al., 2023), such an approach is vastly different from the one used by institutional investors.

Equal weighting mechanically increases exposure to smaller-capitalisation securities compared to a market-weighted benchmark such as the S&P 500, which may amplify the value and size tilts already embedded in the screening methodology. This implies that some of the outperformance or underperformance that we observe could be due to implicit factor exposures rather than the pure effect of the investment strategies themselves.

Another limitation is that the portfolio is rebalanced once every year. This rebalance schedule is aligned with the long-term perspective adopted by the fundamental investment approach, although it does not consider that investors may change their opinions based on new knowledge more often than once each year. Although this approach would help the fundamental strategy to be more responsive, the problem would be higher costs.

Third, it is assumed that all trades are realized at the observed market prices with no liquidity constraints or market impact. This assumption is quite reasonable for large-cap constituents of the S&P 500, but actual execution conditions may be different during times of elevated volatility or market stress.

6.4 Simplified transaction and cost modelling

The transaction cost analysis conducted in this thesis remains intentionally simplified. The sensitivity of the technical strategy to trading costs is assessed for three fixed commission-rate scenarios, 0.1%, 0.25%, and 0.5% per transaction, as summarised in Figure 11.

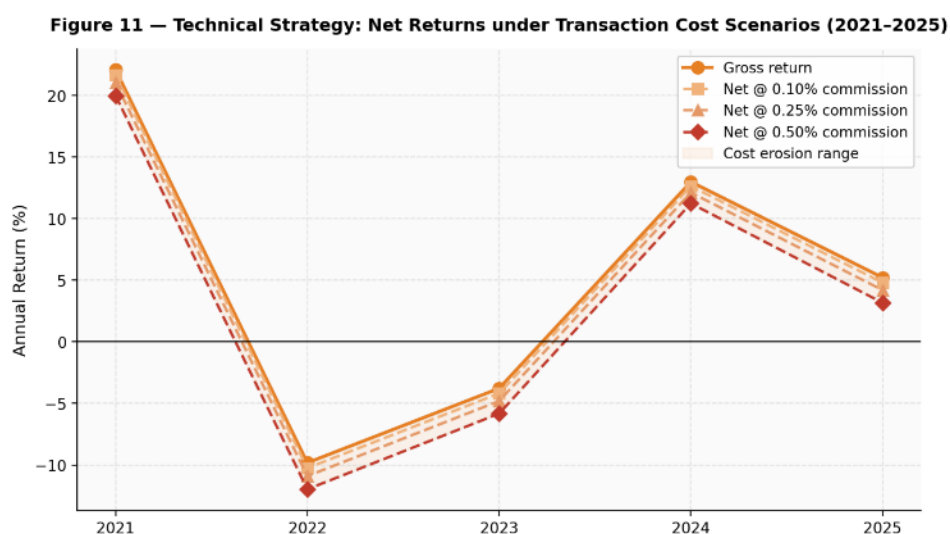


Figure 11 : Technical Strategy: Net Annual Returns under Three Transaction Cost Scenarios (2021–2025). The solid line represents gross returns; dashed lines represent net returns at 0.10%, 0.25%, and 0.50% commission per transaction (avg. 4.0 round-trips/security/year). At 0.25% commission the average net annual return falls from 5.33% to 4.33%, widening the performance gap with the fundamental strategy by a further ~1pp per year.

Source: Author's calculations.

While this framework provides a useful approximation of the impact of trading activity on net performance, it does not fully capture the complexity of real-world implementation costs. However, when put into application, investors experience a wider range of frictions, including bid-offer spread, slippage, taxation, trading impact, partial order fill, and lack of liquidity in stressed market conditions. Such frictional factors are especially pertinent to trending strategies

like the MA50/MA100 cross-over strategy, which results in much higher turnover compared to the buy-and-hold strategy.

A further simplifying assumption is that transaction costs remain constant throughout the sample period, whereas actual trading costs vary considerably across securities, time periods, and market conditions. During periods of elevated volatility, bid-ask spreads tend to widen materially, which would further erode the net returns of active trading strategies. Consequently, the sensitivity analysis presented in Figure 11 likely underestimates the true implementation costs faced by investors in real-world conditions.

6.5 Technical strategy specification

Another important limitation concerns the specification of the technical trading strategy itself. The study relies exclusively on a single MA50/MA100 moving average crossover rule combined with RSI-based contextual interpretation. Although this methodology is grounded in the empirical literature initiated by Brock et al. (1992) and subsequently formalised by Lo et al. (2000), it represents only one possible implementation among a vast universe of technical trading systems.

However, different configurations of moving averages might lead to drastically different outcomes. Shorter moving averages will probably provide better sensitivity during trend reversals and faster re-entry in bear markets but will come with increased whipsaw and false signals when the price is trading in ranges. Long-term moving averages, like the MA200, may help with better trend stability but will cause significant delays during abrupt trend reversals.

Like with the moving averages, the RSI is used purely for interpretation purposes and not incorporated in the actual trading system. Implementing alternative strategies that directly incorporate the RSI in decision making might result in more optimal entry and exit points. Advanced technical analysis techniques like volatility filter, adaptive moving averages, breakout systems, or artificial intelligence-driven signal generation could achieve similar effects.

The aim of this thesis is therefore not to find the best technical trading strategy, but to study the behaviour of a representative and transparent trend following framework in realistic market conditions.

6.6 Benchmark and factor limitations

Although the study compares the two strategies against SPY, IWD, and IWF benchmarks, the analysis remains limited in its treatment of systematic factor exposures. The screening procedure mechanically creates a strong value tilt due to the selection of low P/E securities, while simultaneously introducing sector concentrations in industries such as financials, insurance, energy, and homebuilding.

Thus, some of the relative performance observed may be due to underlying factor exposures rather than stock-selection skill or technical timing ability. The poor relative performance of both strategies versus the SPY in 2023 and 2024 is closely linked to the phenomenal performance of large-cap technology stocks related to the AI-driven rally, a segment that is largely excluded by the value-oriented screening methodology.

A more sophisticated factor decomposition using the Fama French three or five factor models could help disentangle the amount of returns that are due to systematic exposures versus true strategy specific alpha. Likewise, sector neutral portfolio construction techniques might reduce unintended concentration effects and make the results easier to interpret.

6.7 Absence of hybrid strategy testing

One of the most important implications emerging from the empirical results is that the fundamental and technical approaches seem to have complementary rather than mutually exclusive advantages. The fundamental strategy offers superior long-term returns and better risk-adjusted performance in extended bull markets, while the technical strategy offers substantial downside protection and volatility reduction in adverse market conditions.

However, here we study the two approaches separately and do not formally test hybrid allocation frameworks combining both approaches simultaneously. One concrete example of such a hybrid framework would consist of retaining the annual fundamental screening procedure as the stock selection layer, while superimposing the MA50/MA100 crossover rule as a dynamic risk management overlay. Under this architecture, the fundamental screening would determine which securities to hold, while the technical signal would govern when to hold them, exiting positions upon a Death Cross and re-entering upon a Golden Cross. This division of roles is precisely what Zhu and Sun (2018) advocate, arguing that fundamental criteria are effective at identifying which securities to hold over the long run, while technical signals help improve the timing of entries and exits. Such a hybrid approach could potentially capture the return generation of value investing while limiting drawdowns during bear market phases, addressing the key weakness of each strategy in isolation.

Thus, the absence of hybrid strategy testing is a limitation and an important avenue for future research.

6.8 Further research

Several potential future avenues for research arise from the findings and limitations of this thesis.

First, an expansion of the sample period through several decades would improve significantly the reliability of the results obtained and enable investigation of other market conditions, such as secular bull markets, stagflation periods, and financial crises.

Second, further examination can be done with other technical approaches like volatility adjusted crossover techniques, momentum ranking schemes, or adaptive trend following methods. An interesting study would also involve a sensitivity test of the moving average parameters.

Third, machine learning techniques are a very promising area for further investigation. Han et al. (2021) and DeMiguel et al. (2023) point out that methods such as random forests, gradient boosting, neural networks, and Lasso regression may enhance return predictability by capturing nonlinear relationships among technical indicators, accounting variables, and macroeconomic conditions. A natural extension of the present study could therefore be hybrid machine learning frameworks combining fundamental and technical variables.

Fourth, future research can explore dynamic allocation models that switch between fundamental and technical strategies depending on macroeconomic variables, volatility regimes

or market momentum conditions. Such adaptive allocation rules would be very much in line with the Adaptive Markets Hypothesis developed by Lo (2004).

Finally, it would be interesting to extend the analysis to other equity universes such as international markets, small-capitalisation universes or emerging markets to understand whether the conclusions obtained in this study are specific to large-cap US equities or generalisable to wider financial environments.

7. Conclusion

The thesis evaluated the performance of fundamental and technical methods of investment using the S&P 500 equity stocks from 2021 through 2025. In this regard, the thesis uses the same screened portfolio of 20 securities per annum for the two investment approaches; hence the effect of security selection is eliminated and only that of investment approach remains. There were three hypotheses tested by the thesis, and they included: H1: The use of fundamental approach gives better risk adjusted returns than that of technical approach over the entire research period. H2: Performance of the two approaches varies widely depending on market regime. H3: Neither of the approaches creates economically meaningful alpha compared to the benchmark market.

7.1 Summary of findings

Empirical findings imply that the fundamental approach tends to produce higher performance in comparison to the technical approach in relation to generating returns and risk adjustment. On the basis of the entire data interval, the fundamental investment portfolio is associated with a higher return on an annual basis, greater Sharpe ratio, and greater Sortino ratio, which is consistent with previous research on the benefits of value investing.

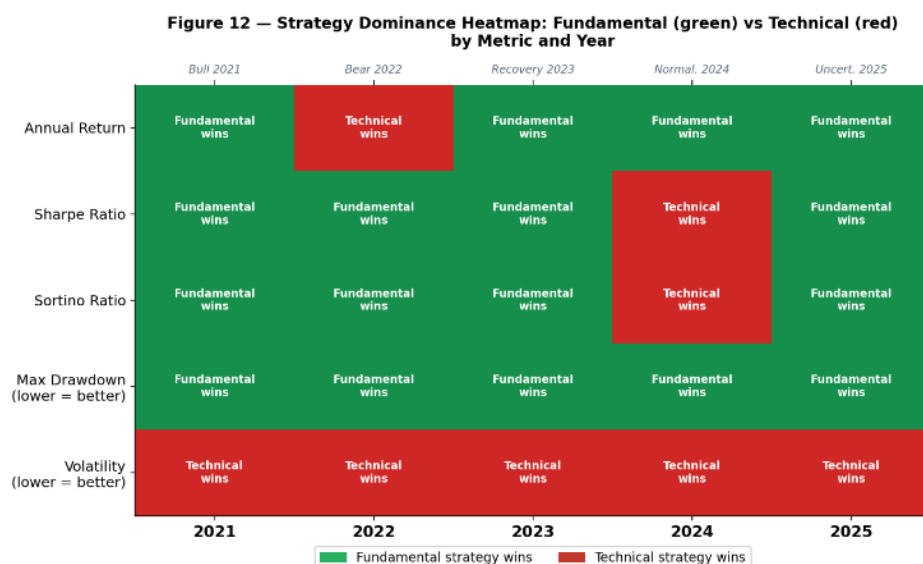


Figure 12 : Strategy Dominance Heatmap: Fundamental vs Technical by Metric and Year (2021–2025). Green cells indicate the fundamental strategy outperforms the technical strategy on that metric in that year; red cells indicate the reverse. Drawdown and volatility are evaluated on a lower-is-better basis. The heatmap confirms the regime-dependent pattern of strategy dominance predicted by the Adaptive Markets Hypothesis (Lo, 2004).

Source: Author's calculations based on Tables 2, 5, and 6.

But the technical approach reveals clear advantages in terms of protection against losses and risk management. For all years analyzed, the Moving Average crossover trading technique is much less volatile and features significantly lower Maximum Drawdowns than the buy-and-hold fundamental approach. These findings demonstrate that trend-following technical signals could serve as a helpful tool for minimizing exposure to financial markets under unfavorable conditions.

The results strongly support H2. The strategy's performance is very different across market regimes. The technical strategy outperforms the fundamental strategy during the 2022 bear market by maintaining cash for extended periods, reducing exposure and limiting losses. The fundamental strategy, in fact, significantly outperforms in the bullish environments of 2021 and 2023 by being fully invested and capturing the upside appreciation of the selected securities. This regime-dependent behaviour is very much consistent with Lo's (2004) Adaptive Markets Hypothesis.

The results in general terms support the Efficient Market Hypothesis as far as H3 is concerned. Neither approach produces economically material alpha after adjusting for market risk and both underperform the passive SPY benchmark over the entire period. The results reinforce the long-standing argument that it is very hard to beat passive indexing consistently when you take into account risk and transaction costs.

7.2 Practical implications

We find that systematic fundamental screening continues to be a robust framework for long-term equity investing, particularly for investors seeking sustained return generation via disciplined value-oriented portfolio construction. At the same time the technical strategy shows significant value as a risk-management tool, which can reduce volatility and drawdowns in adverse market conditions.

The transaction cost sensitivity analysis further highlights the importance of implementation efficiency. The higher turnover of the technical strategy leads to a significant reduction in net performance under realistic assumptions of trading costs and supports the practical virtues of lower turnover investment approaches.

Most importantly, the results suggest that fundamental and technical analysis can be considered as complementary rather than competing methodologies. One possible solution is a hybrid framework that exploits the return generating properties of value investing along with downside protection properties of trend following strategies through technical overlays.

7.3 Contribution to the literature

This thesis adds to the literature by comparing fundamental and technical investment strategies applied to the same screened portfolio of securities directly, to isolate the effect of the investment methodology itself. It also builds upon previous research on the extremely volatile and economically distinct market environment between 2021 and 2025.

Moreover, the study covers a wide range of performance and risk metrics, including Sharpe ratios at the portfolio level, Maximum Drawdowns, rolling volatility, skewness, kurtosis, exposure ratios and transaction cost sensitivity analysis. These additions allow a more complete evaluation of strategy behaviour than traditional return based comparisons.

7.4 Final remarks

The main conclusion of this thesis is that fundamental analysis is not always better than technical analysis (and vice versa) in all market environments. In long bull markets fundamental analysis prevails and generates higher long-run returns, while during times of market distress technical analysis provides better downside protection and lower volatility.

Nevertheless, the results confirm one of the main lessons of modern finance theory ; namely, that it is incredibly hard to earn sustained abnormal gains in extremely competitive environments. Nevertheless, both methods are useful for practical reasons because they offer a structured framework for investing that will allow one to manage risks and avoid falling prey to their own psychological mistakes.

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