FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

EQUITY SCREENING CRITERIA TO CREATE A PROPERLY DIVERSIFIED PORTFOLIO

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RESUMEN

Este trabajo analiza si una estrategia de filtrado de acciones simple y estructurada puede construir una cartera bien diversificada capaz de superar al índice S&P 500. Inspirada en la lógica de modelos de inversión consolidados, la estrategia combina factores de valor, rentabilidad y momentum para seleccionar empresas con fundamentos sólidos y dinámicas de precios positivas.

La metodología de filtrado se aplicó al S&P 500 utilizando datos históricos de los últimos 20 años. La estrategia fue testada con distintos tamaños de cartera y frecuencias de rebalanceo para evaluar su comportamiento a lo largo de diferentes ciclos de mercado. Los resultados muestran que este enfoque estructurado puede generar de forma consistente una rentabilidad superior al índice, lo que destaca el valor de aplicar un proceso de selección disciplinado y lógico en la construcción de carteras de renta variable.

PALABRAS CLAVE

Filtrado de acciones, inversión por factores, valor, rentabilidad, momentum, construcción de cartera, backtesting, comparación con el índice, diversificación, selección de acciones.

ABSTRACT

This thesis examines whether a simple and structured equity screening strategy can build a well-diversified portfolio that outperforms the S&P 500. Inspired by the logic of established investment models, the strategy combines value, profitability, and momentum factors to select companies with strong fundamentals and positive price dynamics.

The screening methodology was applied to the S&P 500 using historical data over the past 20 years. The strategy was tested under different portfolio sizes and rebalancing frequencies to evaluate its performance across market cycles. The results show that this structured approach can lead to consistent outperformance of the benchmark, highlighting the value of applying a disciplined and logical selection process in equity portfolio construction.

KEY WORDS

Equity screening, factor investing, value, profitability, momentum, portfolio construction, backtesting, benchmark comparison, diversification, stock selection.

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1. Introduction

1.1. Study Context

For decades, the investment community assumed that beating the market was nearly impossible. However, Benjamin Graham (1949), considered the father of value investing, showed how fundamental analysis and the identification of undervalued stocks could consistently outperform the market. Shortly after, Harry Markowitz (1952) introduced risk diversification with his Modern Portfolio Theory, which laid the foundation for the Capital Asset Pricing Model (CAPM), later developed by William Sharpe (1964). He proposed a simple mathematic formula to estimate the expected return considering systematic risk and market premium, assuming both an efficient market and rational investors.

This last assumption was later formalized by the Efficient Market Hypothesis (EMH), proposed by Eugene Fama (1970), which suggested that all the available and new information was rapidly factored in stock prices, so neither historical nor fundamental analysis could help to outperform the market. This meant that it was virtually impossible to achieve a premium return over the market that wasn't due to luck.

However, over the years, academic research has demonstrated that by applying certain criteria the market can be outperformed. Therefore, studies regarding value of factor investing have been growing exponentially. For instance, Edward Altman (1968) developed the Z-Score to predict bankruptcy risk by combining different ratios, suggesting that the market was not considering all existing indicators. Robert Shiller (1981) also challenged EMH by demonstrating that stock prices' fluctuations were not fully explained by the expected dividends' effect but also by investor overreaction.

Fama and French (1992), acknowledged that the CAPM was incomplete and introduced their Three-Factor Model (1993) incorporating size and value as drivers of excess return. Around the same time Jegadeesh and Titman (1993), uncovered the momentum effect reflected in how stock with a strong recent performance usually continued to outperform the market in the short-term.

Another major contribution came from Joseph Piotroski (2000), who designed the F-Score to identify financially stable firms within high book-to-market portfolios, showing a significant performance increase. Similarly, Ken Fisher (2007), proposed valuation filters like the Price to Sales Ratio and the Price to Research Ratio to find undervalued growth companies with R&D

potential. Shortly after, Joel Greenblatt (2010) introduced his "Magic Formula", combining Return on Capital (ROC) and earnings yield, to rank companies with strong fundamentals; meanwhile, Novy-Marx (2013) highlighted gross profitability as a reliable predictor of returns, reinforcing the idea that certain quantitative filters can help to outperform the market.

As a result, the combination of value, quality and momentum has become central in factor investing. Studies like Asness, Moskowitz and Pedersen (2013) proved that the observation of these factors can yield return and mitigate risk. Likewise, Reschenhofer (2023) has shown that applying such multifactor combination systematically can surpass both the market and single-metric models. All in a nutshell, the latest evidence suggests that markets are only partially efficient, better described by the Adaptive Market Hypothesis developled by Andrew Lo (2004), which considers them to be constantly learning and evolving.

1.2. Objectives

The main objective of this thesis is to explore whether a structured and disciplined combination of equity screening factors can lead to the construction of a portfolio that consistently outperforms a benchmark index.

The strategy is inspired by the logical sequencing proposed in academic literature and widely used in professional investment models. The aim is to test whether following a value–profitability–momentum order provides a meaningful edge in stock selection.

Specifically, the project seeks to:

- Define a consistent framework for filtering stocks based on academic research.
- Choose an index, a weighting method, and a rebalancing frequency as part of the investment strategy.
- Build a diversified portfolio that beats the benchmark by applying structured selection criteria.
- Analyse total return, sector contributions, and risk metrics, comparing the portfolio both to the benchmark index and to an ETF that replicates it.
- Study the behavior of the strategy under different market conditions and sector dynamics.
- Evaluate the strategy's ability to generate alpha, reduce risk, or improve risk-adjusted returns over time.
- Use the R programming language to analyse the strategy and the main key metrics.
- Conclude whether the combination of filters and structure used provides a replicable advantage over passive investing.

1.3. Justification of the Topic's Selection

The decision to focus this project on equity screening and portfolio construction came from a combination of academic interest and practical motivation. From the beginning of my studies in business and finance, I've been especially drawn to investment strategies that are both data-driven and grounded in theory. The idea of outperforming the market by applying structured filters to a broad index like the S&P 500 seemed not only intellectually challenging, but also highly relevant in today's investment landscape, where active and passive strategies constantly compete for efficiency.

This topic also offered the opportunity to connect academic literature with real-world tools. By using Bloomberg to apply filters and R for performance analysis, I was able to test whether ideas from researchers like Fama, French, Greenblatt, or Piotroski could be translated into an actual strategy. That connection between theory and application felt especially meaningful, as it reflects the kind of work done in the asset management industry. It was important for me to choose a topic that didn't just explore financial concepts, but also helped me develop skills and tools I could actually use in a professional context.

Finally, the personal motivation came from wanting to understand what truly drives long-term returns. The current financial environment is full of noise -endless data, opinions, and short-term volatility- and I wanted to explore whether a disciplined, logic-based approach could still generate consistent outperformance. The challenge of reducing a massive index like the S&P 500 to a smaller portfolio with better performance was both ambitious and rewarding, and that's ultimately what made this topic the right choice for my final project.

1.4. Methodology

The methodology of this study begins with a review of academic papers and relevant literature in the field of factor investing. The objective of this initial step is to identify a structured and evidence-based framework for applying equity screening filters. From this research, a logical sequence of selection criteria is defined—focusing on value, profitability, and momentum—as suggested by many leading studies in the field. These filters are not applied mechanically, but rather as guiding principles to shape a consistent stock selection strategy.

Once the theoretical structure is established, an investment strategy is developed. This includes the choice of an index from which stocks will be selected, the study of the portfolio size, and the selection of a weighting scheme. The filters are applied in a sequential and logical order to reduce the initial universe of stocks to a manageable and diversified portfolio. Sector and accounting considerations are taken into account to improve the comparability and reliability of the filters.

The resulting portfolio is backtested using historical data over a 20-year period. The performance of the strategy is analysed using the R programming language, which enables precise evaluation of returns, volatility, and other key performance metrics. In addition to comparing the portfolio against the chosen benchmark index, further analysis is carried out against an ETF that replicates the benchmark. The performance is also studied across sectors, evaluating the contribution of each sector to the total return and identifying which areas drive the strategy's success.

The final part of the methodology involves drawing conclusions based on the observed results. These conclusions aim to assess whether a structured factor-based strategy -built on simple yet consistent logic- can outperform the market over time, and under which conditions it performs best. The study also discusses the limitations of the approach and outlines possible improvements or extensions for future research.

2. What is a Sufficiently Diversified Portfolio?

A portfolio is sufficiently diversified when the investment is spread across a selection of assets that are not highly correlated, in order to reduce exposure to firm or sector-specific events. This methodology is very attractive for risk-averse investors, especially when market conditions become unpredictable.

Benjamin Graham (1949) argues that diversifying does not only mitigate risk but also increases the chances at getting a superstock. In globalized markets, Burton Malkiel (2020) sustains that diversification can still offer high benefits despite increasing correlation among international assets; even partial diversification across different regions can help to reduce volatility.

Additionally, Ramón Bermejo Climent (2021) demonstrated that even in periods of monetary tightening or persistent labour market destruction, the thoughtful application of screening criteria can help to absorb systematic shock.

2.1. Systematic vs Diversifiable Risk?

The difference between systematic and diversifiable risk is one of the main principles of modern portfolio theories. Systematic risk refers to macroeconomic factors that impact the whole financial market and cannot be eliminated through diversification, including interest rate changes, inflation, recession and political uncertainty. This type of risk is inherent in the market structure and affects all assets to varying degrees. In contrast, diversifiable risk is related to factors unique to a particular company or sector, which can be significantly reduced through portfolio diversification. Idiosyncratic risk includes, for example, management changes, production issues, or sector regulation.

Sharpe (1964), through the Capital Asset Pricing Model (CAPM), formalized the idea that only systematic risk should be compensated with higher expected returns, reinforcing the relevance of filtering out diversifiable risk through the construction of a portfolio. Furthermore, Ramón Bermejo Climent (2021) emphasized that properly distinguishing these two risk categories is key to designing effective screening models, especially during volatile periods when systematic risks dominate.

These past years, Campbell, J., et al. (2022) have offered empirical evidence on the relationship between systematic and idiosyncratic risk. Using long-term data, they note that recent increasing stock correlations have made diversification less effective, especially during crises like the 2008 financial crash and the pandemic. These findings reinforce the importance of accounting for diversifiable risk in portfolio construction and equity screening strategies.

Liu, Y., and Zhu, Y. (2023) deepen the understanding of diversifiable risk by distinguishing between "good" and "bad" idiosyncratic volatility. They show that not all firm-specific volatility is detrimental: some reflects positive information or innovation and is associated with higher future returns, while other forms signal uncertainty or operational risk and are penalized by the market. This adds value to equity screening strategies, as it allows for a more selective approach that differentiates beneficial idiosyncratic signals from harmful noise, improving portfolio construction beyond traditional risk metrics.

In conclusion, effective portfolio management depends on the identification and minimization of diversifiable risk, while accepting and pricing systematic risk appropriately.

2.2. Number of Stocks

Literature has not reached a consensus on the exact number of stocks required to achieve sufficient diversification. In his letter to partnership, Warren Buffet (1960) advised against overloaded portfolios -over 15 stocks- stating that they reflect lack of conviction. Early studies by Evans and Archer (1968) suggested that most of the diversifiable risk could be eliminated with only 8 to 10 stocks.

Later, Elton and Gruber (1977) demonstrated that portfolios with more than 30 stocks still achieve significant risk reduction, challenging the sufficiency of 10-20 stocks and highlighting that diversification continues to add value, even if the risk decreases more gradually. Statman (1987) expanded on this by arguing that borrowing investors may require at least 30 stocks and lending investors 40, emphasising the relevance of investor's goals and behavioural factors.

Based on S&P analysis, Newbould and Poon (1993) questioned the standard 8-20 recommendation, considering it may be insufficient for most investors as individual risk varies widely. Similarly, Adamiec et al. (2019), using S&P simulations, reported a very significant risk reduction when increasing portfolio size from 10 to 25 stocks. Ross et al. (2017) confirmed that while standard deviation declines with more assets, the marginal reduction in risk slows over time.

More recently, Eccles et al. (2021) proposed that the optimal number of stocks should be adjusted based on market capitalization: large-cap portfolios may be well-diversified with 15 assets, whereas small-cap portfolios require around 26. Zaimovic et al. (2021) concluded that there is not a universal optimal number of stocks –it highly depends on the market conditions, maturity, investor preferences and risk measurements methods. While emerging markets offer fewer diversification opportunities and therefore require less stock, developed markets may need portfolios with over a hundred.

Finally, a study conducted by Can Li (2022) showed that when the portfolio size reached 12 stocks, 88.45% of the diversifiable risk was eliminated; however adding more provided minimal additional benefit while increasing complexity and costs.

3. Portfolio Criteria

3.1. Index Selection: S&P 500

The S&P 500 is a solid starting point for building and testing stock portfolios because it combines enough variety with ease of use. Since it includes 500 large U.S. companies, it offers a broad sample for applying filters and diversifying, without being so large that it makes data processing too slow or complicated. All companies in it are required to follow SEC regulations, which means they publish their financial data regularly, in standard format and updated for the required frequencies. This is very convenient for equity screening as the data is more structured, plus, since the data is updated monthly, quarterly, or yearly, it allows for testing different rebalancing frequencies to see what works best.

Another advantage is that the index covers all industries, which helps reduce the risk of concentrating the portfolio in one specific sector. Also, the stocks in the S&P 500 are highly liquid, which means they can be bought and sold easily. That makes strategies based on valuation, profitability, or momentum more practical, since there's less risk of issues when executing trades.

Finally, because the S&P 500 is one of the most widely used benchmarks in finance, it makes sense to use it as a reference when the goal is to build a portfolio that aims to outperform the market.

3.2. Time Frame

Choosing the right time period is crucial to achieve a well-diversified portfolio that outperforms the market both in bull and bear timings. The past 20 years offer a wide variety of situations-from crises to recoveries-and show how the Federal Reserve (Fed) has adjusted monetary policies to meet its dual mandate: containing inflation and increasing employment rate.

The housing market crisis in 2008 led the Fed to lower interest rates and ease the monetary policy, in order to stabilize the job market while inflation stayed low. The recovery from the Great Recession was slow but steady: the Fed maintained low interest rates and engaged in multiple rounds of quantitative easing to support growth. A notable episode came in 2013 when the Fed announced that it might start slowing down bond purchases, to which investors reacted strongly, showing how sensitive financial markets were to its policy. Later, the Fed raised interest rates as the economy strengthened, but the trade tensions with China and signs of global growth, led to rate cuts in 2019 to mitigate uncertainty.

Then in 2020, the COVID-19 pandemic forced the Fed to act quickly, cutting rates to zero and restarting emergency programs to avoid a collapse in employment. Shortly after, in 2021, inflation rose sharply due to supply issues and energy price increases. The Fed focused on keeping inflation under control by steadily raising interest rates up to 5%, even if it risked slowing employment.

This past year, the central bank started lowering interest rates again as a response to inflation easing. However, Trump's reelection plus the potential imposition of tariffs have created a lot of uncertainty in the markets, and the Fed has had to pause rate cuts and wait to evaluate the effect of this instability on inflation trends.

Using this 20-years time frame is especially valuable to backtest the performance of our portfolio across periods of unpredictability, crisis and economic boom. Otherwise, it would be biased and less applicable to new situations -which is the final aim of this study.

Given this context of shifting monetary conditions and recurrent uncertainty, it becomes essential to integrate macroeconomic indicators into portfolio construction. One such tool is the Sahm Rule, developed by economist Claudia Sahm (2019), to detect the start of a recession using labour market data. The rule is triggered when the average unemployment rate of the last 3 months increases by at least 0.5% above the lowest value in the previous 12 months. This indicator reacts quickly to turning points in the economic cycle, warning about economic recession without relying on stock prices. Its simplicity and historical reliability have made it a very useful indicator for investment strategies.

Since it has proven to be effective in past cycles, we believe it can improve our portfolio performance analysis. For this reason, we will consider the Sahm Rule in our analysis, in order to evaluate if the portfolio is well diversified in both recession and economic boom periods.

3.3. Sector Filtering

In the construction of an equity portfolio, it is necessary to take into account that some industries are structurally and financially different from the rest of the market. For this reason, firms operating in the financial and real estate sectors will be excluded from the investment universe, in order to avoid inefficient deviation and misrepresentation.

Financial companies function under specific accounting rules and are influenced by regulatory frameworks. Their capital structures rely on high leverage, and many key financial indicators -like debt ratios- do not carry the standard interpretations present for the other industries. As Graham (1949) notes, they require different treatment due to the nature of their assets and the dependency on regulatory framework. Furthermore, Altman's Z-Score (1968), was originally developed to be applicable to "manufacturing" corporations. He decided to exclude financial institutions from the analysis due to the different dynamics followed by their balance sheets and liquidity ratios.

Real estate companies, especially REITs, will also be excluded from our portfolio due to their atypical financial structure. Greenblatt (2010) argues that REITs have limited reinvestment capacity due to their obligation at distributing dividends. This could distort profitability and growth metrics used in standard models. In addition, they are often evaluated based on sector-specific metrics such as asset appreciation and rental income, making traditional criteria less applicable.

The F-Score (Piotroski, 2000) also assumes industrial-style financial statements. This metric relies on profitability, leverage, and operating efficiency indicators, so applying it to firms with sector-specific accounting treatment, like banks or real estate firms, can lead to inconsistent or misleading conclusions. Novy-Marx (2013) also highlights that many quality and profitability metrics -such as the gross margin ratio- are not meaningful for financial firms, due to their unusual structure of their income statements and the nature of their assets and liabilities. Finally, Bermejo Climent (2021) also reinforces this idea, noting that excluding these entities enhances the interpretability and reliability of screening models based on accounting ratios.

By excluding these two sectors, the strategy focuses on companies with comparable accounting structures, ensuring that fundamental filters are applied consistently. It also avoids introducing macroeconomic noise related to interest rate cycles and monetary policy sensitivity -factors that disproportionately affect financial and real estate firms.

3.4. Rebalancing Frequency

Rebalancing refers to the process of updating the stocks conforming a portfolio by reapplying the equity screening criteria. As market conditions change, some of the stock may drop out of the portfolio because they no longer make it through the filter requirements, while other new stocks may qualify. The frequency of this process can significantly influence overall returns and strategy responsiveness to fluctuations in the market.

Given that the SEC requires all companies within the S&P 500 to file structured and standardized financial statements on a quarterly basis (10-Q) and annually (10-K), it is possible to analyse and compare different rebalancing frequencies using consistent data. These reports are stored in structured form and ensures data availability and completeness. Unlike other indices or smaller firms where gaps or delays in reporting might occur, the S&P 500 provides a dependable data source. This consistency minimizes calculation errors when tracking portfolio evolution and improves the accuracy of performance analysis. All of this greatly simplifies the process of analysis and backtesting against the benchmark.

3.5. Weighting Schemes

After applying the equity screening criteria and defining the rebalancing methodology, the next step is determining how capital is allocated among the chosen assets. This is referred to as the weighting scheme, and it has a direct effect on both the performance and the risk of the portfolio. The most common approaches are value weighting and equal weighting.

In the first method, each company's market capitalization drives the capital allocation of the portfolio, meaning larger firms receive a greater share. Traditional models assume that the market holds the optimal portfolio structure so, given that the market allocation investment depends on the companies' market cap, they use this weight-value approach. However, Fama & French (1992) showed that there are small-cap and mid-cap stocks that turn to be more profitable than what the market predicts, and likewise, there are large-cap companies which actually offer lower returns than expected.

An equal-weighted portfolio assigns the same weight (1/N) to all stocks, regardless of its market capitalizacion. This exposure increases the presence of mid-cap and small-cap companies, which have historically shown more long-term excess returns. Apart from being more diversified, when a portfolio uses the equal-value methodology, the size of the companies no longer has an effect on its performance results. Therefore, since no large company dominates these results, it is simpler to analyse if the selected criteria is actually adding value.

Several studies have explored this further. Both Chen et al. (2012) and Plyakha et al. (2014) showed that portfolios based on equal-weighting outperformed value-weighted ones, in terms of return. DeMiguel et al. (2016) added that these naive strategies often perform better than optimized ones, mainly because of estimation errors in mean-variance models. Qin & Singal (2021) found that even though equal-weighted portfolios achieve higher average returns, they come with higher risk, suggesting the combination with factor models as a solution.

Reschenhofer (2023) extended the argument by showing that simple 1/N weighting schemes combined with value, momentum, and profitability factors can beat complex optimized models out-of-sample. Simplicity in portfolio construction makes the model less likely to be overfitting and, therefore, more applicable to new situations.

Finally, recent working papers (Cirulli & Walker, 2024) challenge the idea that equal-weighted portfolios are hard to beat. They show that by removing a small percentage of stocks with the highest volatility or the lowest momentum, it is possible to build enhanced versions of equal-weighted portfolios that deliver better ratios and lower drawdowns.

When considering all these theories, we have decided to use the equal-weighting approach for the portfolio construction. It supports a more balanced portfolio, eliminates the impact of market-cap on results and makes it easier to analyse the effectiveness of the screening criteria. It also, reflects the academic consensus favoring simple allocation methods, while we also recognise that simple enhancements like those proposed in 2024 may offer future improvements.

4. Equity Screening

Equity screening is a systematic approach for filtering a wide universe of stocks to select those with desirable investment characteristics. This process combines ratios and metrics to reduce the initial index to a subset of companies that meet the selected criteria. In this methodology, three core factors will be used: value, profitability, and momentum. They will be combined sequentially to improve performance of the portfolio, measured in terms of return and risk.

4.1. Value

The value factor aims to identify and invest in cheap stocks, referring to stocks trading below their intrinsic value, suggesting that they are under-priced in comparison to fundamental metrics. This strategy assumes that the market is not always efficient because it does not always quickly absorb all the available information. There are some over-valued and under-valued companies, and this can be used to enhance the performance of our portfolio.

In this section we will study value-approach methodologies developed by different authors. The objective is to justify the convenience of the filters that we used in our equity screening.

4.2. Profitability

The profitability factor identifies companies with strong internal performance, ensuring that value is not derived from distressed or low-margin operations. Novy-Marx (2013) introduced gross profitability (gross profit / total assets) as a superior predictor of returns compared to traditional earnings. Greenblatt's Return on Capital (ROC) is also widely used to identify firms that efficiently allocate their resources. The inclusion of profitability filters helps avoid value traps by distinguishing truly undervalued firms from those priced low due to weak business models. This approach is supported by Fama and French (2015), who included profitability in their five-factor model. The most common metrics used are Return on Assets (ROA), gross profitability, and various Return on Capital definitions.

Moving on to more recent finding, a study conducted by Niessen-Ruenzi, A., et al. (2018), analyses whether the probability that a firm is committing accounting fraud can be used as a screening criterion to improve stock selection. To estimate fraud risk, the authors use a model based on financial statement data, originally developed by Dechow et al. (2011), that calculates a fraud "F-score." This score is based on factors such as abnormal accruals, changes in profitability, and recent equity or debt issuance. Using data from the U.S. stock market between 1996 and 2012, the authors sort firms into decile portfolios according to their predicted fraud probability and rebalance monthly. Their results show that stocks in the highest fraud risk decile underperform those in the lowest decile by 1.11% per month. A long-short strategy that buys low-risk and sells high-risk stocks delivers an annualized alpha of over 10%, even after adjusting for common risk factors like those in the Fama-French model.

This study shows that fraud risk is not properly priced by the market and can be a strong anomaly. For screening purposes, the fraud F-score can offer a valuable filter to eliminate firms that appear financially solid but may be manipulating earnings. This enhances profitability filters by helping investors avoid firms with artificially inflated fundamentals.

4.3. Momentum

Momentum exploits the empirical observation that stocks with strong past performance tend to continue outperforming in the short term. Jegadeesh and Titman (1993) demonstrated that momentum, especially using 6-to-12-month windows, can significantly improve returns.

Bianchi, D., et al. (2022) studied a well-known issue in momentum strategies: they can suffer severe losses during market reversals, known as momentum crashes. The authors show that the returns of momentum portfolios have negative skewness, especially during recessions or recovery periods. They propose a new method that adjusts portfolio exposure based on the time-varying skewness of returns, not just volatility. The study uses U.S. data from 1927 to 2020, analysing the daily returns of traditional momentum portfolios. They propose a model that estimates skewness dynamically using a statistical distribution and adjusts the portfolio weight accordingly. During periods of high negative skewness, the strategy reduces exposure to avoid large drawdowns. Their approach improves the Sharpe ratio and reduces downside risk compared to other popular momentum management strategies, such as volatility scaling.

For screening purposes, this paper shows that not all momentum signals are equal -some carry significant downside risk. By incorporating a skewness filter, investors can avoid trades with high crash probability, enhancing the reliability of momentum-based stock selection.

Momentum acts as a complementary filter to value and profitability, particularly effective in mitigating the lag between accounting data and market pricing.

4.4. Authors' Study

4.4.1. Altman Z-Score

Altman's Z-Score (1968) is a financial model that combines five ratios to estimate bankruptcy risk. The linear function would be the following:

$Z = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E$

A. Working Capital / Total Assets
B. Retained Earnings / Total Assets
C. EBIT / Total Assets
D. Market Value of Equity / Total Liabilities
E. Sales / Total Assets

This metric represents a very useful filter, especially in equity screening, to eliminate financially fragile companies from the universe, thereby reducing risk. Interpretation of the score follows this guideline:

- $Z > 3.0$ → The company is financially healthy and unlikely to go bankrupt in the short term.
- $1.8 < Z < 3.0$ → Commonly known as the "grey zone". The company must be analysed because it does face some financial risk.
- $Z < 1.8$ → The company is likely to go bankrupt in the next two years.

Despite its age, the Z-score remains widely used due to its simplicity, transparency, and strong empirical track record. The metric was initially intended to measure only manufacturing firms' financial health, therefore excluding financial institutions. However, several revised versions of the original score have been developed to adapt it to different types of firms and economic contexts. One of the most widely used is the Z'-Score, which excludes variable D, market value of equity, making it applicable to private firms. Another adaptation is the Z"-Score, designed for non-manufacturing companies, especially those in the service sector.

4.4.2. Benjamin Graham

Graham (1949), a pioneer of value investing, introduced strict criteria for identifying firms which are fundamentally sound and undervalued by the market. These include the establishment of floors for firm size, conservative capital and long-term earnings stability.

Two of the most basic criteria Graham proposed was selecting firms of adequate size and with a consistent dividend history. He argued that larger companies which have been paying dividends for at least 20 years, tend to offer greater stability and lower volatility.

For earnings stability, Graham looked backwards at a 10-year interval and required a 30% cumulative growth in Earnings per Share (EPS). Graham also proposed that valuation ratios should remain within conservative bounds: Price to Earnings (P/E) ratio should not exceed 15, and the Price to Book (P/B) ratio should remain below 1.5.

Furthermore, Graham developed a valuation formula to estimate intrinsic value:

$$\mathrm{V} = \frac{\mathrm{EPS} * (8.5 + 2g)}{\mathrm{AAA}}$$

EPS = earnings per share

g = expected growth rate

AAA = yield on high-grade corporate bonds.

Regarding leverage, Graham emphasized on avoiding overly indebted firms. Bermejo (2021) proposes using the Interest Coverage Ratio (EBIT/Interest Expense > 5) as a reliable proxy for financial health.

Finally, Graham's most important qualitative idea is the "margin of safety". He suggests buying stocks significantly below their intrinsic value, requiring a minimum discount from their estimated fair value, normally around 30%. He also proposed that valuation metrics like Price to Earnings and Price to Book Value should be combined to ensure margin of safety.

4.4.3. Joel Greenblatt

Joel Greenblatt's (2010) approach to equity screening is rooted in the idea that investing doesn't require complexity, but consistency. He proposes a systematic strategy that combines two fundamental financial principles: quality and value of a company. He quantifies quality through return on capital (ROC), an indicator of how efficiently a firm uses its resources to generate profits; and valuation via earnings yield, which measures how cheap a stock is relative to its earnings.

Greenblatt's "Magic Formula" is a ranking mechanism: firms are ranked from best to worst in this two metrics (ROC and earnings yield). Then, the ranks are combined, and the stocks with the best joint scores are selected. This dual ranking allows investors to focus on companies that are both profitable and undervalued. What makes the formula compelling is its simplicity and empirical validation. Over extended time periods, this strategy has shown consistent outperformance over market benchmarks.

Recent empirical research further extends the application of the Magic Formula to new environments. Vestre and Wikheim (2022) adapt the strategy to the Norwegian stock market, confirming that its principles remain effective even in smaller, less liquid contexts. Their findings propose several practical adjustments to improve the Magic Formula in real-world settings. These include limiting the impact of outliers by smoothing the most extreme values, redefining profitability using gross profit instead of EBIT, and factoring in transaction costs. These changes help make the strategy more realistic and robust without changing its original structure, showing that the Magic Formula can still perform well across different market environments.

4.4.4. Ken Fisher

One of the most distinctive contributions to equity screening was proposed by Ken Fisher (2007), who introduced a value-based investment strategy focused on uncovering temporarily undervalued growth stocks. This methodology stands out by combining valuation metrics with an emphasis on future profitability rather than solely relying on historical earnings.

Fisher's method relies mainly in the Price to Sales Ratio (PSR), which he uses instead of more traditional indicators like P/E or P/B. The PSR measures a company's market capitalization relative to its revenue, providing a broader and often more stable perspective on value. A low PSR can indicate undervaluation, especially in firms where earnings are temporarily depressed due to operational or cyclical issues but revenues remain strong.

Fisher also proposes what he calls the "Glitch": a concept that describes companies going through short-term difficulties that blurs their long-term value. This could mean, for example, a growth company experiencing a temporary slowdown, leading to stock price drops that are disproportionate to its actual business fundamentals.

In addition to the PSR, Fisher uses another metric known as the Price to Research Ratio (PRR), which is particularly relevant in industries where R&D spending is a major driver of long-term value, such as biotech or tech. The PRR measures how much investors are paying per dollar of R&D expense, so undervalued firms often appear with low PRRs, suggesting potential future upside not yet priced into the market.

To apply Fisher's approach, one typically filters for companies with:

- PSR significantly below 1 (depending on the industry)
- Solid revenue levels even if earnings are weak
- Consistent or increasing R&D investment (if relevant)
- And signs that the company is only temporarily out of favor

Bermejo (2021) argues that this methodology is especially useful in volatile markets where price tends to deviate more frequently from intrinsic value. Fisher's model doesn't just seek cheap stocks; it seeks mispriced growth stocks with the potential to recover strongly once the market corrects its temporary misjudgment.

4.4.5. Piotroski

The F-Score, developed by Piotroski (2000), is a fundamental screening method created to help investors select stocks with strong financial positions. It focuses especially on value stocks, aiming to separate those with real potential from those that might be fundamentally weak, even if they appear cheap.

This method consists of nine binary criteria divided into three main categories: profitability, leverage/liquidity, and operating efficiency. Each criterion gives 1 point if the company meets it and 0 otherwise, with the total score ranging from 0 to 9. A higher score suggests a healthier company.

The first group, profitability, includes the following measures:

1. Return on Assets (ROA) > 0: the company has positive net income.

2. Cash Flow from Operations (CFO) > 0: the firm generates positive cash flow from its operations.
3. Change in ROA > 0: ROA has improved compared to the previous year.
4. Accruals: CFO > ROA, meaning that earnings are supported by cash flow and not just accounting figures.

These indicators help to identify whether the firm is actually generating profits and if its financial performance is improving. One of the key ideas from the paper is that many value stocks are cheap because they are not profitable, and this part of the score filters those out.

The second group, leverage and liquidity, focuses on:

5. Change in Long-term Debt Ratio < 0: the proportion of long-term debt has decreased.
6. Change in Current Ratio > 0: short-term liquidity has improved.
7. No new shares issued: the firm has not issued new equity over the past year.

Piotroski explains that companies in poor financial condition often take on more debt or issue new equity, which can dilute shareholder value. These criteria make sure the company is improving or at least maintaining a stable financial structure.

The last group is operating efficiency:

8. Change in Gross Margin > 0: gross profitability has increased.
9. Change in Asset Turnover > 0: the company is using its assets more efficiently to generate revenue.

According to Piotroski, these measures help detect whether the firm is becoming more efficient in its operations, which is important for long-term value creation.

By combining these three areas, the F-Score gives a fuller picture of the company's financial health beyond just valuation multiples. Bermejo (2021) highlights that this score is especially useful when applied to value stocks, because it helps avoid those that are "cheap for a reason", in other words, companies with weak fundamentals that might not perform well even if they are undervalued.

Hyde (2014) tests the Piotroski F-Score in emerging markets and finds that it still works well outside the U.S. Stocks with high F-Scores (>=8) earn significantly higher returns than stocks with low scores (<=2). Interestingly, the F-Score signal works for both small and large companies, and is even stronger when financial data is recent or combined with momentum or value strategies.

4.4.6. The Conservative Formula

The Conservative Formula, developed by Van Vliet and Blitz (2018), is a quantitative investment strategy that selects 100 stocks based on three key criteria: low volatility over the past 36 months, high net payout yield (which includes dividends and share buybacks minus new share issuance), and positive price momentum over the past 12 months excluding the most recent month. These stocks are chosen from the 1,000 largest companies, and the portfolio is equally weighted and rebalanced every quarter.

The aim of the strategy is to give investors efficient exposure to proven factor premiums such as low risk, value, and momentum, using only simple price and dividend data. According to Van Vliet and Blitz, the Conservative Formula achieved a compounded annual return of 15.1% from 1929 to 2016, outperforming the market while maintaining lower volatility.

One of the main strengths of the formula is its simplicity. It avoids complex accounting measures, does not require short selling or leverage, and can be applied across large, liquid stocks. The authors show that it performs well not only in the US but also in Europe, Japan, and emerging markets. It also remains effective across different economic environments.

4.4.7. Intangible Value

The Intangible Value factor, developed by Eisfeldt et al. (2022), is a refinement of the traditional value investing approach. It adjusts the Book to Market ratio by incorporating estimated intangible assets, such as brand value or human capital. These intangibles are calculated using a method based on accumulated SG&A (Selling, General & Administrative) expenses. The authors argue that traditional value metrics often misclassify companies by ignoring these assets, especially in sectors like tech or healthcare where intangibles dominate.

To build this enhanced value signal, the authors add intangible capital to book equity and then sort companies by industry before calculating value scores. This helps to correct for sector-level accounting differences. The result is a new value factor that maintains the pricing power of the classic Fama-French factor but delivers significantly higher returns. Backtests show that firms classified as “cheap” under this revised method are typically more profitable, productive, and financially sound than those flagged by traditional value screens. The factor is especially effective in more recent periods when traditional value strategies have struggled.

4.4.8. Enhanced Portfolio Optimization

Larsen (2022) applies an Enhanced Portfolio Optimization (EPO) model to factor investing, focusing specifically on value stocks. The model is based on the work of Pedersen et al. (2021) and aims to improve how stocks are weighted in a factor-based portfolio. Instead of using equal or cap-weighted methods, EPO adjusts weights based on expected returns and risk, using a version of mean-variance optimization. In Larsen’s implementation, the value factor is constructed at the industry level to avoid biases and enhance signal precision.

The study uses a backtesting period from 1963 to 2020, applying the EPO framework to US stocks. Results show that optimized value portfolios significantly outperform traditional ones, with Sharpe ratios as high as 0.87 compared to 0.38 for the original Fama-French value factor. The model is robust across different market conditions, including recessions. One key insight is that optimization does not change the factor itself but improves how it is implemented. For investors using value signals, whether based on accounting measures or other screens like Piotroski or Altman, EPO provides a practical way to improve performance without altering the underlying logic of the strategy.

4.5. Value – Profitability – Momentum Logic

The sequence in which factors are applied -starting with value, followed by profitability, and ending with momentum -has both a logical and quantitative justification. Empirical studies show that filtering in this order improves both portfolio returns and risk-adjusted performance compared to other combinations.

For instance, Novy-Marx (2013) demonstrated that while value strategies offer strong long-term returns, many of the cheapest stocks are fundamentally weak. He found that combining value with gross profitability leads to significantly higher Sharpe ratios. In his results, a portfolio combining gross profitability and value achieved a Sharpe ratio of 0.66 in large caps and 0.80 in small caps, compared to 0.45-0.55 when each factor was used alone. This supports the earlier foundational findings by Fama and French (1992), who showed that value stocks -

particularly those with high earnings yield or low Price to Book- consistently outperform, and also aligns with Graham's (1949) view of value investing as a way to obtain a margin of safety. Greenblatt (2010) reinforced this logic by combining value and return on capital in his "Magic Formula", emphasizing that cheap, efficient businesses generate superior results over time. Applying profitability after value thus ensures that selected firms are not only undervalued but also economically efficient.

Momentum is applied last because, unlike value and profitability, it is a short-term, fast-moving signal that reflects how the market is reacting to recent information. Using it earlier in the sequence could result in selecting firms that are trending but fundamentally weak. Jegadeesh and Titman (1993) found that a 6-month formation and 6-month holding momentum strategy yielded over 1.0% monthly excess returns, but these returns were more volatile and often reversed after a year. This means momentum can enhance performance, but only when used as a confirmation layer after filtering for intrinsic value and operational strength. Reschenhofer (2023) confirmed this in a multifactor backtest: portfolios using the value-profitability-momentum order achieved annual returns of 19.1% and a Sharpe ratio of 0.65, outperforming unstructured combinations. Importantly, this ordering also reduced turnover by 50%, improving cost efficiency. This structured approach is supported by the work of Asness, Moskowitz, and Pedersen (2013), who found that combining value, quality, and momentum signals across global markets leads to more robust and diversified portfolios.

In sum, applying value first reduces the universe to underpriced stocks; profitability then filters out structurally weak firms; and momentum ensures the remaining stocks are also supported by market sentiment. This structured approach is not only theoretically sound, but also statistically optimal based on multiple large-scale studies.

While the implementation does not replicate any single existing model, the selection and sequencing of the filters used in this strategy are strongly inspired by the extensive literature on factor investing. The theoretical frameworks developed by Altman, Piotroski, Graham, Greenblatt, and others have contributed valuable insights into how value, profitability, and momentum can be combined to enhance portfolio performance. Building on this foundation, the criteria applied in this project aim to reflect the same underlying investment principles, translated into a practical and data-driven structure adapted to the Bloomberg environment.

4.6. Criteria Selection

To construct a robust equity portfolio capable of outperforming the market, we used the EQS (Equity Screening) function from Bloomberg. This tool allows for the creation of customized filters based on a wide set of financial metrics and market data. The screening was applied to the S&P 500 index, given its representativeness, liquidity, and the availability of structured and comparable financial statements. From this initial universe, we excluded companies in the Financial and Real Estate sectors due to the incompatibility of their financial structures with standard screening metrics, as highlighted in previous literature.

The resulting portfolio, formed by the top-ranked stocks based on the selected criteria, was then tested against the S&P 500 benchmark using historical data starting from January 1st, 2005. A quarterly rebalancing frequency was applied (every four months), which aligns with the SEC's financial statement filing schedule. The portfolio used an equal-weighting scheme, allowing each selected stock to have the same capital allocation, thereby neutralizing size effects and simplifying performance attribution to the filtering process itself.

Table 1: Equity Screening Criteria

General
Universe: S&P 500
Sector Exclusion: Financials and REITs
Value
EV/EBITDA (TTM) < 20
FCF Yield > 3%
Profitability
ROIC > 6%
Gross Margin > 20%
Momentum
30-day Price momentum (top 25)

The equity screening strategy applied in this portfolio is structured around the sequential combination of value, profitability, and momentum filters. Each criterion selected plays a specific role in narrowing down the investment universe to a smaller group of stocks that are not only undervalued, but also operationally strong and currently favored by the market. This multifactor approach is supported by decades of empirical evidence demonstrating that combining these three signals improves performance over using them in isolation.

The universe selected for analysis is the S&P 500 index. This index is ideal for testing systematic investment strategies because it includes a broad and diverse sample of large, liquid companies that comply with standardized accounting rules and regulatory requirements, ensuring the availability of reliable and consistent data. The exclusion of financial firms and real estate investment trusts (REITs) is essential due to their sector-specific accounting practices and capital structures. As mentioned earlier, according to Graham (1949) and Greenblatt (2010), these sectors distort traditional financial metrics and require different valuation models. Novy-Marx (2013) also highlights that many profitability filters lose meaning in these sectors, reinforcing the decision to exclude them.

The first quantitative filter applied is EV/EBITDA < 20. This ratio evaluates how cheap a company is in terms of its operational earnings before accounting effects like depreciation or capital structure. It offers a more standardized way to compare firms across sectors and is commonly used as a valuation proxy in value investing strategies. The threshold of 20 aligns with conservative value screening principles, reducing exposure to overpriced firms. The rationale follows Benjamin Graham's (1949) principle of applying strict valuation limits to ensure margin of safety. Greenblatt (2010), in his Magic Formula, also uses earnings-based valuation as one of the two pillars for ranking stocks.

Next, the filter Free Cash Flow Yield > 3% is used. Free cash flow provides a more robust measure of financial health than earnings because it reflects the actual liquidity generated by a business. Setting a minimum of 3% ensures that firms not only appear cheap but also have the financial strength to reinvest, repay debt, or return capital to shareholders. Furthermore, Bermejo (2021) supports the inclusion of cash-based valuation metrics as part of quality-enhancing filters that avoid value traps, especially during volatile periods.

The third filter is Return on Invested Capital (ROIC) > 6%. ROIC is widely regarded as a key profitability metric, as it shows how effectively a company turns capital into profits. This ratio is central to Greenblatt's (2010) Magic Formula, which ranks companies based on ROIC and earnings yield to select businesses that are both cheap and efficient. According to Fama and French (2015), profitability is a fundamental driver of long-term returns.

Another profitability criterion included is Gross Margin > 20%. Gross margin measures the firm's core operational profitability before overhead and financing costs. Novy-Marx (2013) demonstrated that gross profitability has similar predictive power to traditional value factors, especially in large-cap stocks. By requiring a margin over 20 percent, the strategy ensures the company has real pricing power and a sound business model. This step complements ROIC and provides a layer of operational quality to the portfolio.

Finally, to capture market sentiment and trend-following behavior, the last filter applies a momentum criterion: selecting the stocks with the highest 30-day price change. The momentum effect was first documented by Jegadeesh and Titman (1993), who showed that stocks with strong past returns tend to continue performing well in the short term. Momentum is applied after value and profitability filters to confirm that selected companies are also receiving market recognition. This sequence is important: applying momentum last ensures that fundamentally weak firms temporarily trending upwards are excluded.

The full structure aligns with the academic consensus that combining value, profitability, and momentum results in more robust and stable portfolios than relying on any single factor alone. Fama and French (1992, 2015), Novy-Marx (2013), and Reschenhofer (2023) all provide evidence that each of these factors contributes independently to returns. When applied sequentially and supported by rational thresholds, they create a filtering mechanism capable of selecting stocks that outperform the market not by chance, but through identifiable and repeatable characteristics.

5. Analysis and Inference of Results

5.1. Portfolio Performance vs Benchmark

5.1.1. General Performance

Figure 1: Cumulative Return (Portfolio vs Benchmark)

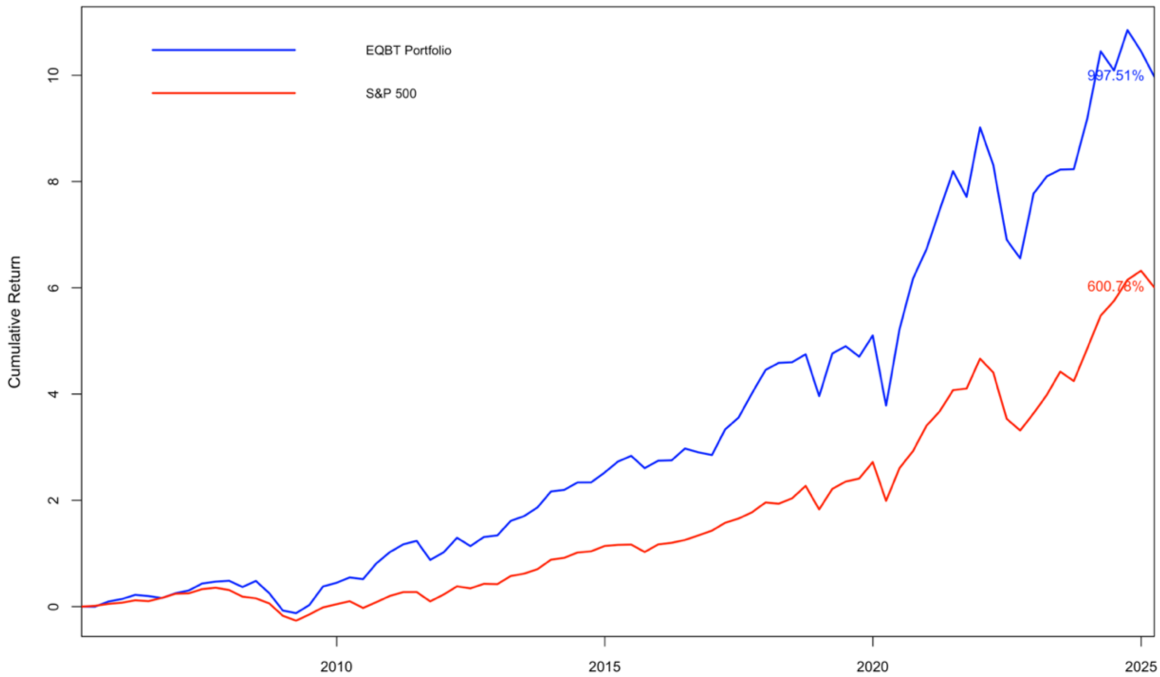
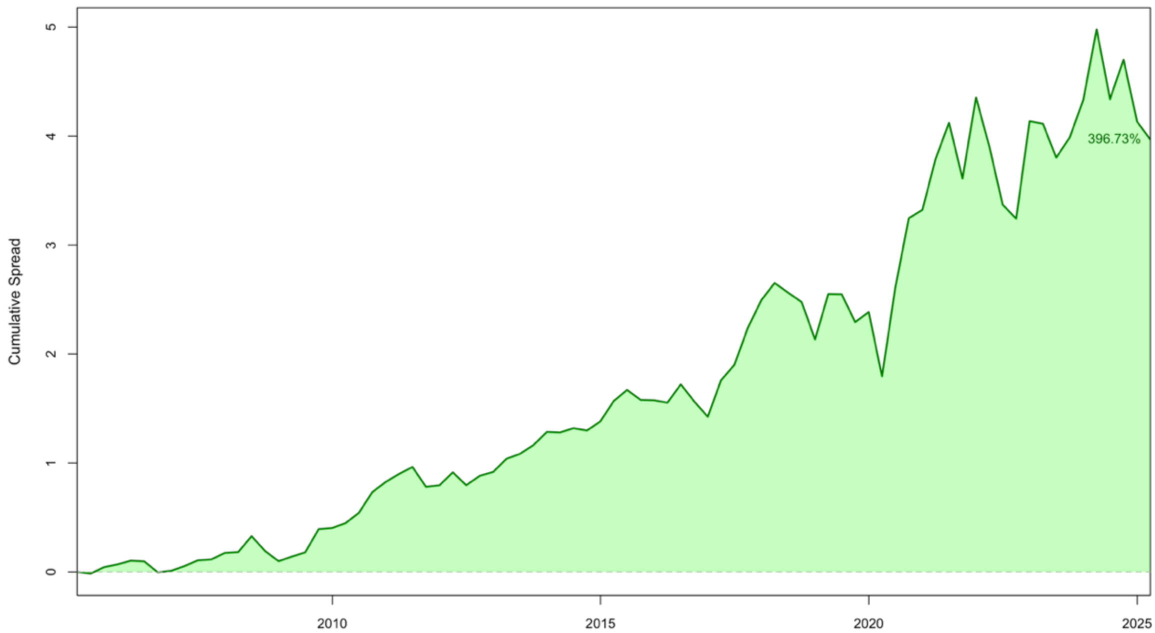


Figure 2: Spread (Portfolio vs Benchmark)



The first chart shows the cumulative return of the constructed portfolio compared to the S&P 500 over the period 2005–2025. The EQBT portfolio significantly outperforms the benchmark, reaching a total return of 997.51% versus 600.76% for the index. The second chart displays the cumulative spread between the two strategies, confirming a consistent and widening outperformance, particularly from 2019 onwards. With a cumulative excess return of nearly 400%, the results validate the effectiveness of the value–profitability–momentum screening strategy and its robustness across different market cycles.

Table 2: Key Portfolio Metrics

Metrics	Value	Brief Interpretation
Total Return (%)	997.51	Cumulative return well above the benchmark
Benchmark Return (%)	600.78	S&P 500 return over the same period
Spread Return (%)	396,73	Excess cumulative return over the benchmark
Mean Return (%)	15.15	High average annual return
Mean Active Return (%)	3.25	Average annual return above the benchmark
Minimum Return (%)	-21.40	Worst annual return recorded
Maximum Return (%)	21.77	Best annual return recorded
Standard Deviation (%)	18.57	Annual volatility
Semi Variance	14.24	Downside risk (only negative deviations)
Tracking Error (%)	8.66	Deviation from the benchmark
Skewness	-0.22	Slightly left-skewed (sharper drops than rises)
Sharpe Ratio	0.74	Excellent risk-adjusted return
Jensen Alpha	4.51	Return above CAPM expectations
Information Ratio	0.32	Return per unit of active risk
Beta	0.87	Lower volatility than the market
Correlation	0.90	High correlation with the benchmark

The portfolio delivers a mean annual return of 15.15%, which not only reflects strong absolute performance but also significantly exceeds typical market averages over long periods. This is reinforced by a mean active return of 3.25%, indicating that the strategy consistently generated returns above the S&P 500 benchmark. Such excess performance suggests that the factor-based screening logic has been effective in identifying companies with superior long-term potential.

In terms of risk, the portfolio shows a standard deviation of 18.57%, which signals a moderate level of volatility typical of equity-based strategies. However, what's particularly relevant is that despite this volatility, the portfolio maintains strong performance metrics, showing that returns were not achieved by assuming excessive risk. The minimum annual return of -21.40% marks the most adverse year during the backtesting period. While this may appear high, it is expected in equity markets, especially during periods of crisis. The maximum return of 21.77%, on the other hand, highlights the portfolio's capacity to fully capitalize on bullish market phases. The negative skewness of -0.22 implies a slightly asymmetric return distribution, with a greater tendency toward sharp negative returns than positive spikes. This is not uncommon in momentum-based strategies, which can suffer short-term losses during market reversals. It also suggests that downside protection mechanisms could be considered in future iterations.

The Sharpe Ratio of 0.74 indicates a strong risk-adjusted return. This means that, for each unit of risk taken, the strategy provided substantial excess return over the risk-free rate, surpassing the conventional threshold (0.5-0.6) used in portfolio management to identify "efficient" strategies. Moreover, the beta of 0.87 suggests that the portfolio is less volatile than the overall market, while still capturing most of its upward movements. This slightly defensive profile enhances its attractiveness for risk-conscious investors, especially when combined with the high absolute and relative returns.

Together, these metrics confirm that the strategy achieves an effective balance between return and risk. It consistently outperforms the benchmark while maintaining lower market sensitivity and delivering solid risk-adjusted results. The factor-based filtering approach not only adds value in terms of raw performance, but also ensures that this performance is delivered efficiently and with controlled volatility.

5.1.2. Turnover Analysis

Figure 3: Number of Stocks per Rebalancing Period

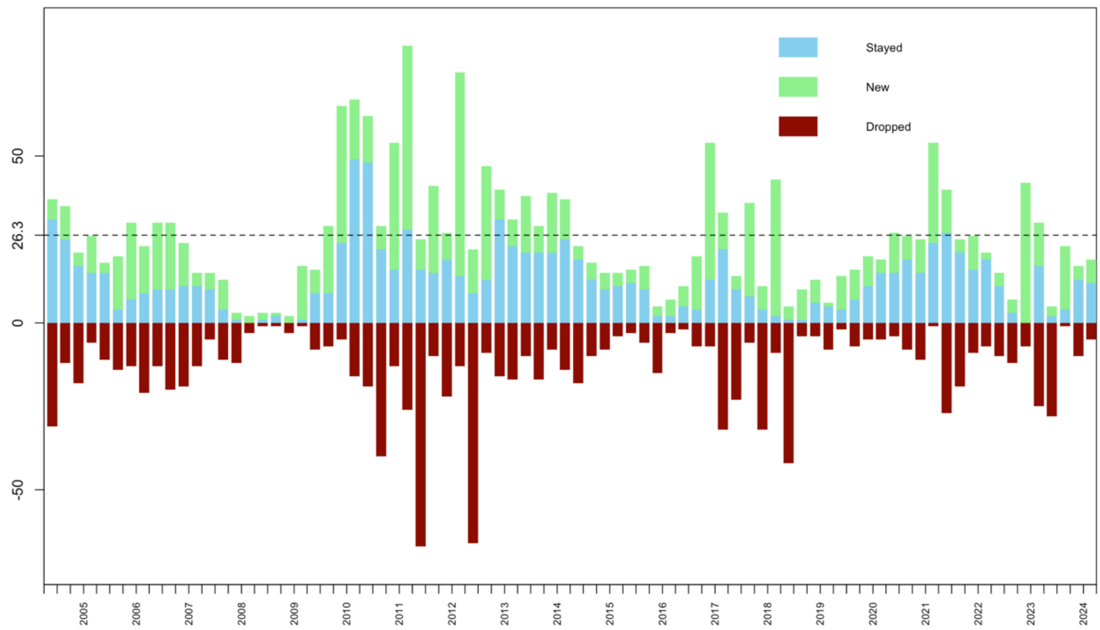


Figure 3 shows the number of stocks retained, added, and removed in each rebalancing period. On average, the portfolio holds around 26 stocks, with visible fluctuations depending on market conditions. Periods like 2009–2012 show higher turnover, likely driven by economic stress and recovery, while more stable periods show fewer changes.

The frequent entry and exit of stocks reflects the responsiveness of the strategy to updated fundamentals and price trends, especially through the value-profitability-momentum sequence. Despite the turnover, a stable core of companies tends to remain, indicating consistency in the screening logic.

5.1.3. Macroeconomic Changes

Figure 4: Portfolio Return and Recession Periods

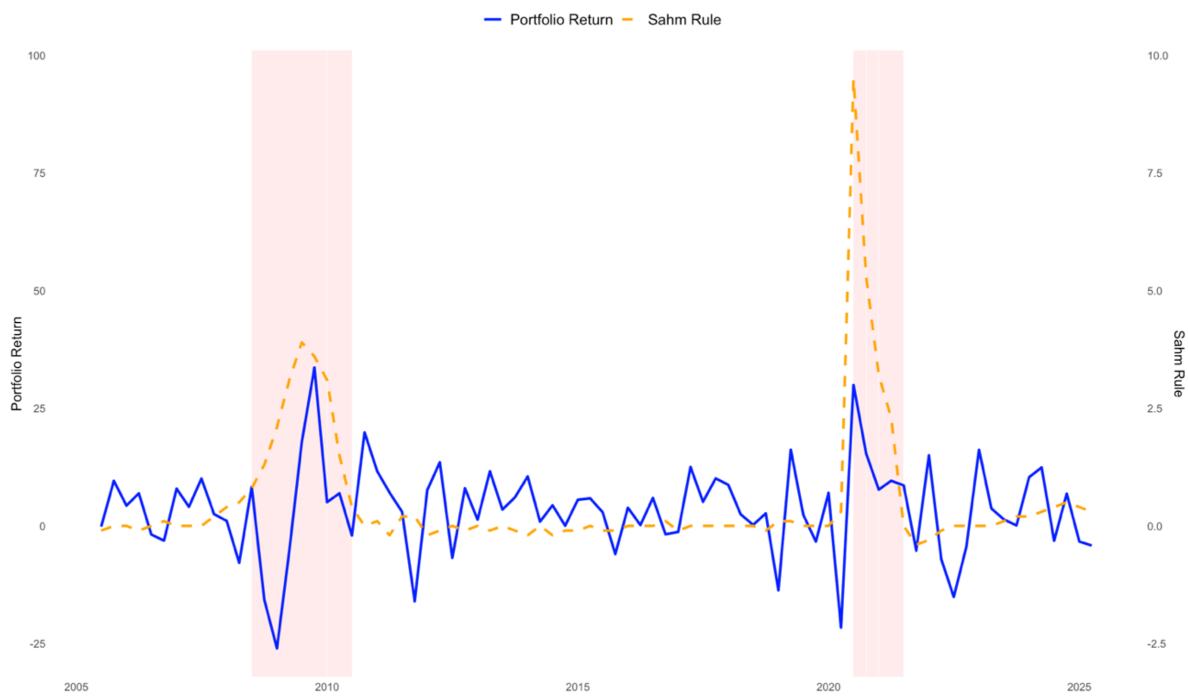


Table 3: Recession Metrics

	Mean (%)		Volatility (%)		Sharpe Ratio	
Recession	Portfolio	SP500	Portfolio	SP500	Portfolio	SP500
No	2.84	2.59	7.78	6.97	0.36	0.37
Yes	7.27	3.89	17.0	12.6	0.42	0.30

Figure 4 illustrates the portfolio's quarterly returns compared to the Sahm Rule, an early recession indicator based on changes in the unemployment rate. The shaded areas mark periods where the Sahm Rule was triggered, capturing the 2008 financial crisis and the COVID-19 recession. During both episodes, portfolio returns became more volatile but recovered quickly, showing no evidence of sustained underperformance. This suggests the screening approach is able to adjust exposure effectively when macroeconomic conditions deteriorate.

The table confirms that the portfolio performs better than the S&P 500 during recession periods. It achieves a higher Sharpe Ratio (0.42 vs 0.30), meaning that returns per unit of risk are stronger even though volatility is higher. In normal market conditions, the performance is more in line with the benchmark, with both showing similar Sharpe Ratios and moderate returns. This indicates that the portfolio adds the most value when market stress is high.

In summary, the strategy shows strong defensive properties during recessions, supported by both macro indicators and performance metrics. While its behaviour during stable periods could be improved, for example by fine-tuning the momentum filter or adjusting exposure during low-risk phases, the ability to outperform during downturns demonstrates the robustness of the factor-based selection model.

5.2. Portfolio Performance vs ETF

Figure 5: Cumulative Return Portfolio vs ETF

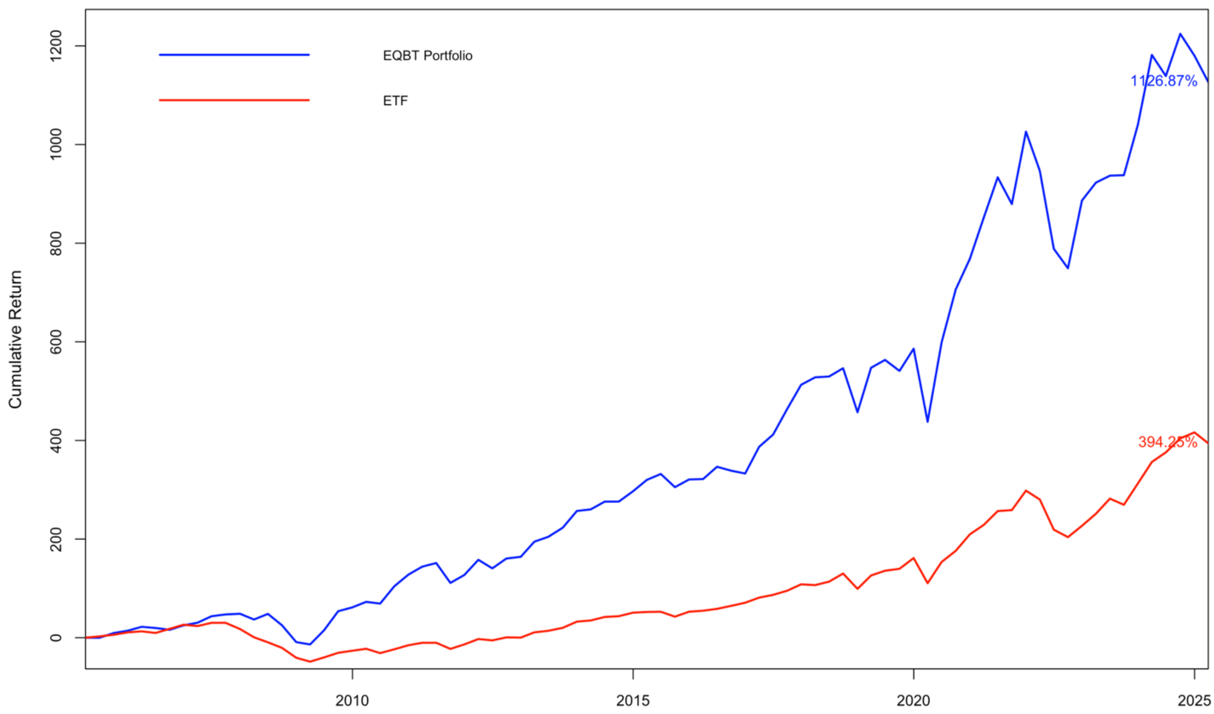


Figure 6: Spread Portfolio vs ETF

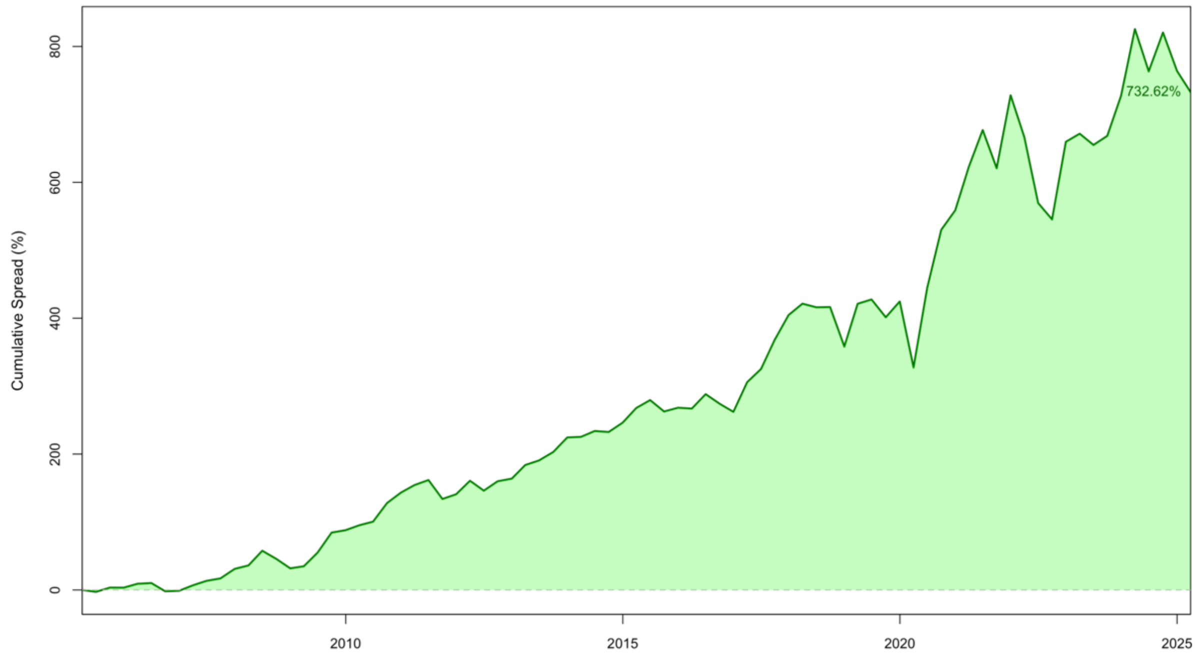


Table 4: Return, Risk and Return/Risk Metrics

Return	**Portfolio**	**SP500**
Total Return (%)	1016.44	355.10
Maximum Return (%)	15.71	11.19
Minimum Return (%)	(13.10)	(11.92)
Mean Return (Annualized) (%)	22.61	14.25
Risk		
Standard Deviation (Annualized)	22.41	19.73
Downside Risk (Annualized)	16.20	14.47
Skewness	(0.10)	(0.35)
VaR 95% (ex-post)	(2.09)	(1.83)
Return/Risk		
Sharpe Ratio	0.63	0.42

The reason for comparing the EQBT portfolio with a passive ETF, in addition to the S&P 500 index, is to make the analysis more realistic. While the index is commonly used in academic studies, real investors usually invest through ETFs that replicate the index. These vehicles involve real-world elements like fees, liquidity, and trading constraints that aren't reflected in the index itself. By including the ETF as a benchmark, the comparison gives a clearer picture of how much added value the active strategy provides in practical terms, not just on paper.

Unlike the earlier comparison with the index, which was based on quarterly data, the results here are based on daily returns. This means that the metrics -such as volatility, downside risk, and Sharpe Ratio- may differ slightly, as they capture short-term fluctuations and day-to-day market noise that quarterly data smooths out. This also gives a more detailed picture of how the portfolio behaves in real time.

Looking at Figures 5 and 6 and the performance table, the EQBT portfolio clearly outperforms the ETF across all key metrics. It ends the period with a cumulative return of 1126.87%, while the ETF reaches 394.25%. The spread chart confirms that this difference builds up consistently over time, not just during short-term rallies, and reaches a 730% gap by the end of the sample.

In terms of annualised returns, the portfolio delivers 22.61%, much higher than the ETF's 14.25%. While this comes with slightly more volatility (22.41% vs 19.73%) and downside risk (16.20% vs 14.47%), the Sharpe Ratio of 0.63 versus 0.42 shows that the portfolio offers a significantly better return per unit of risk.

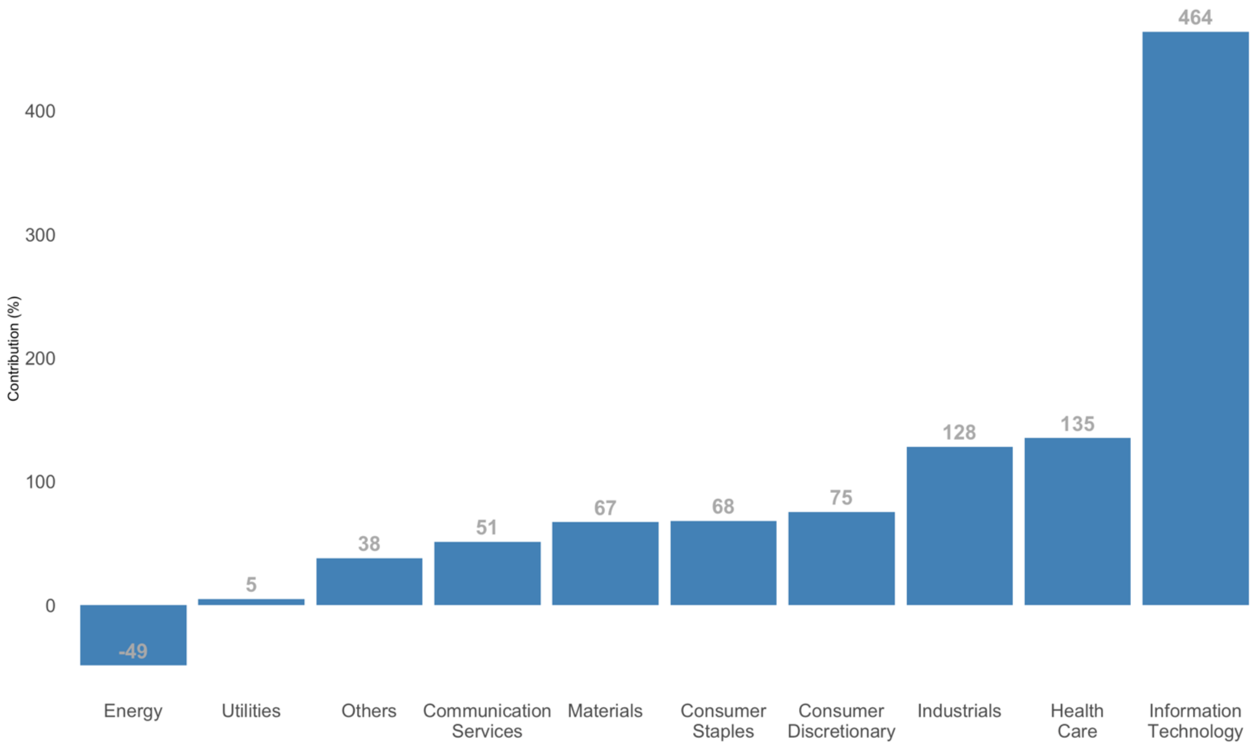
The Value-at-Risk is a bit worse for the portfolio (-2.09%), which reflects greater short-term risk exposure, but this is compensated by its stronger long-term performance. It's also worth noting that the portfolio has a lower (less negative) skewness (-0.10 vs -0.35), meaning its return distribution is more balanced, and less tilted toward extreme negative outcomes. This adds another layer of robustness to the strategy.

In summary, the EQBT portfolio clearly beats the ETF both in terms of total return and efficiency. The factor-based screening approach not only finds better-performing stocks, but also manages risk well over the long run. While there's room to improve risk control during periods of high volatility, the results show that the strategy adds real value compared to passive investing.

Whether daily or quarterly data produce "better" ratios depend on the objective. Daily data gives more precise, real-time risk estimates and captures short-term dynamics. However, it can also be more sensitive to market noise. Quarterly data smooths out this noise and better reflects long-term trends. In this case, the consistency of results across both frequencies suggests the strategy performs well under both lenses.

5.3. Sector Analysis

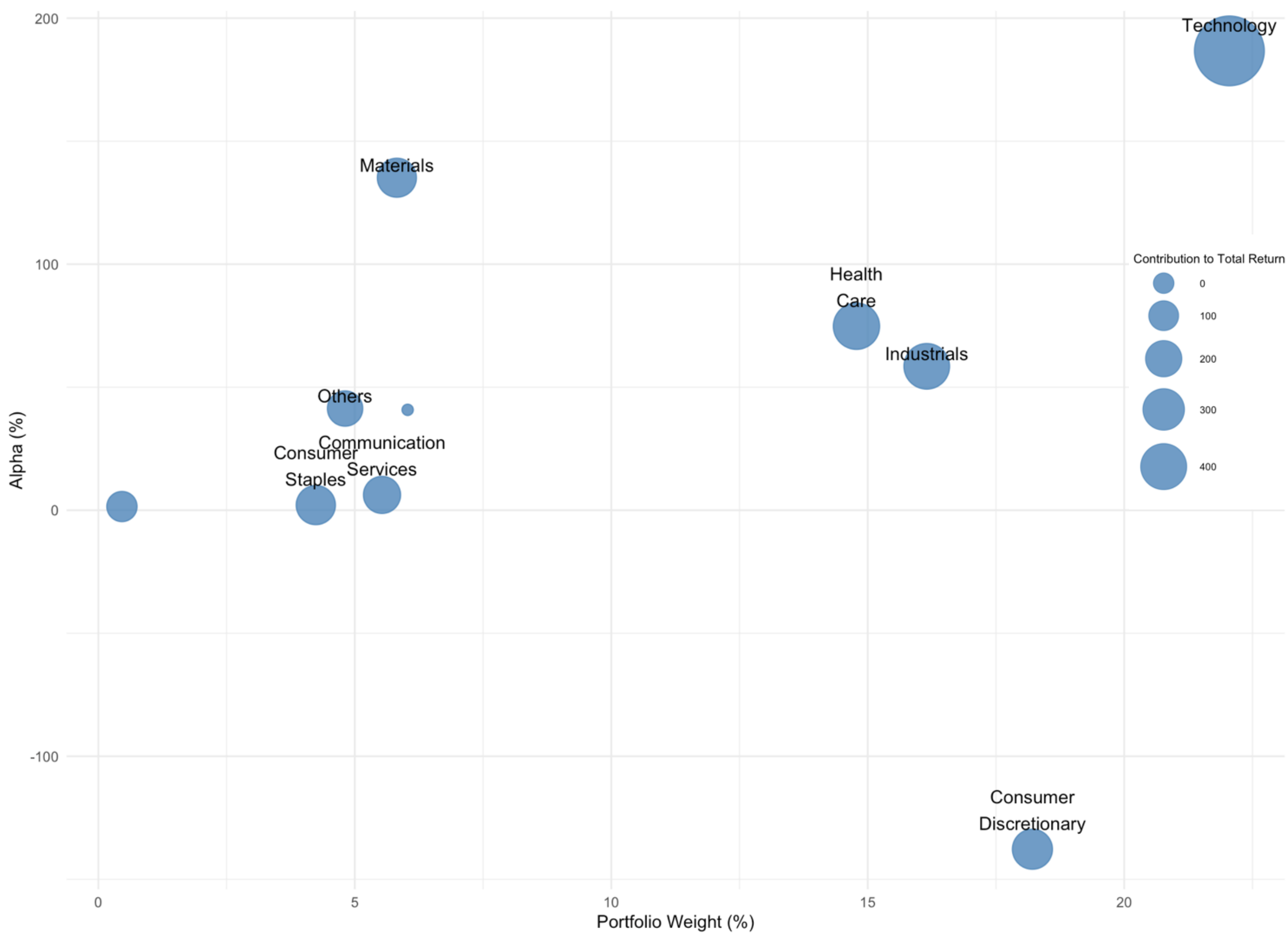
Figure 7: Contribution to Total Return per Sector



Information Technology stands out as the main driver of performance, with a contribution of 464%, far exceeding all other sectors. Health Care and Industrials also played key roles, contributing 135% and 128%, respectively. These sectors tend to host companies with strong fundamentals and growth potential, which aligns well with the value–profitability–momentum logic applied in the screening process.

On the other end, the Energy sector had a negative contribution of -49%, being the only sector that detracted from performance. This may reflect the sector's high volatility, structural instability, or the fact that selected energy stocks underperformed despite passing the filters. Other sectors like Utilities, Consumer Staples, and Communication Services contributed positively, but to a much smaller extent. Overall, the return profile is concentrated in a few sectors that consistently produced outperforming stocks.

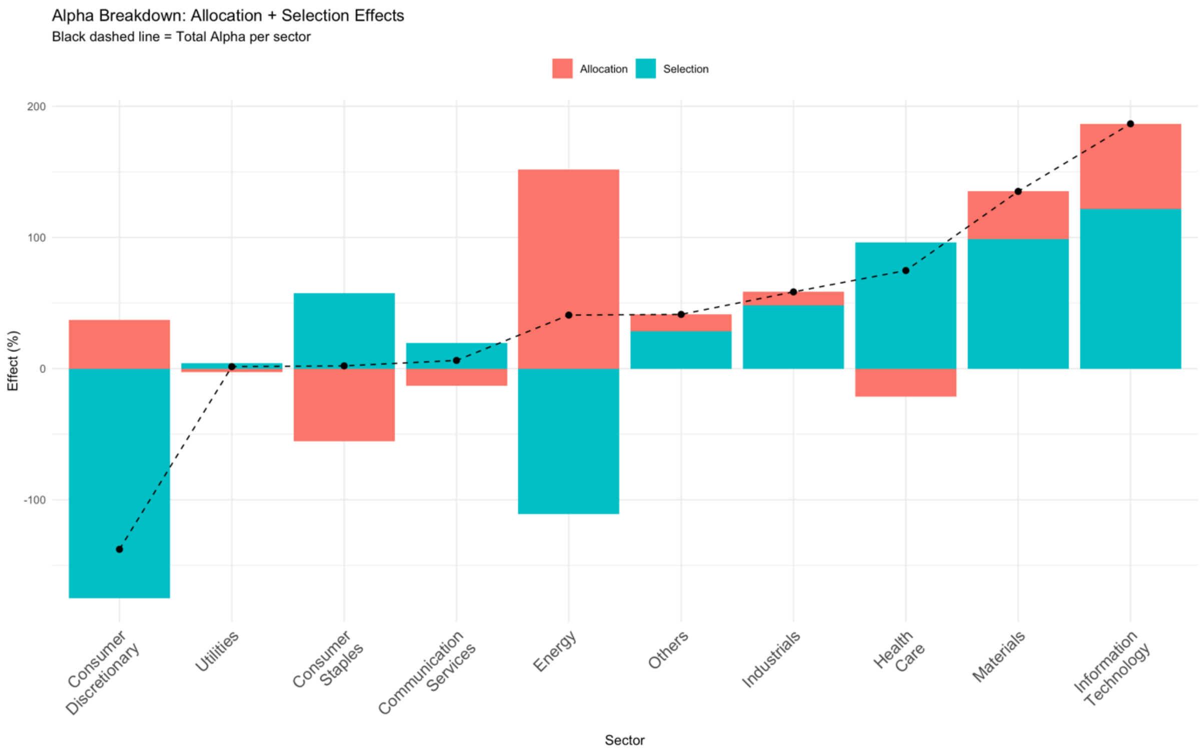
Figure 8: Alpha vs Weight by Sector



This chart plots sector alpha against portfolio weight, with the bubble size reflecting each sector's contribution to total return. Information Technology stands out again -not only does it have the highest weight and highest alpha, but it also dominates in return contribution, as seen in the large bubble. This means that both the decision to allocate heavily to the sector and the strong performance of its stocks were key to the portfolio's overall success.

Industrials and Health Care also appear in the upper-right quadrant with moderate to high weights and solid alpha, supported by sizable bubbles, showing that they contributed meaningfully to returns as well. In contrast, Consumer Discretionary had a relatively large weight but negative alpha and low contribution, suggesting inefficiency in stock selection. Meanwhile, sectors like Materials and Communication Services show decent alpha with lower weight and smaller bubbles, meaning they were well selected but had a limited impact on the total return due to their lower presence in the portfolio.

Figure 9: Alpha Breakdown by Sector



The black dashed line shows the total alpha for each sector. Information Technology once again leads with a strong contribution from both selection and allocation, indicating that both the decision to overweight the sector and the specific stocks chosen within it were successful. Similar patterns are seen in Materials and Industrials, where most of the alpha came from strong stock selection.

Interestingly, Energy shows a high allocation effect but a deeply negative selection effect, confirming that while the portfolio invested heavily in the sector, the specific stocks picked underperformed. Consumer Discretionary also shows a negative total alpha, driven mainly by poor selection. On the positive side, sectors like Health Care and Communication Services show strong selection effects even with modest allocations, meaning the few names included were well chosen.

Taken together, the three charts reveal that the portfolio's strong performance was driven not just by sector allocation, but by effective stock selection within key sectors like Technology, Health Care, and Industrials. The strategy's filters successfully captured high-quality names in those areas, while also avoiding or limiting exposure to some underperforming segments.

However, the negative alpha in sectors like Consumer Discretionary and Energy highlights room for improvement. These cases suggest that the filters may need refinement for certain industries, or that additional metrics could help avoid false positives. Despite this, the overall picture is one of a well-balanced, fundamentally driven strategy that delivers value through both intelligent exposure and careful selection.

6. Conclusions

After conducting this analysis, we can conclude that the strategy we designed -based on a structured sequence of value, profitability, and momentum filters- has successfully met its goal: outperforming the S&P 500 and its ETF alternative over a 20-year period. Inspired by the academic frameworks of authors like Graham, Piotroski, and Greenblatt, we adapted their ideas into a practical screening methodology that was then applied through Bloomberg. Although we did not directly replicate their models, their logic clearly shaped the approach and helped us build a solid foundation for the equity selection process.

From a performance standpoint, the portfolio delivered outstanding results. It consistently outperformed both the benchmark index and the ETF in cumulative return, total alpha, and risk-adjusted metrics like the Sharpe Ratio. The robustness of the portfolio was especially visible during recession periods, where it maintained better Sharpe Ratios and higher average returns than the S&P 500, even in environments of high volatility. These results suggest that the screening logic was not only effective in selecting high-quality stocks, but also in adapting to changing macroeconomic conditions.

Sector-level analysis confirmed that the strategy captured most of its value from well-positioned and high-growth areas like Information Technology, Health Care, and Industrials. The results show that alpha was driven not just by allocating more to those sectors, but by choosing the right stocks within them. On the other hand, some underperformance in sectors like Consumer Discretionary and Energy revealed that the model might be less effective in industries that are more cyclical, sentiment-driven, or exposed to unpredictable external shocks.

Although overall performance was strong, there is still room for improvement. Certain filters may require fine-tuning to better adapt to sector-specific dynamics, especially in areas where traditional valuation or profitability ratios may not fully reflect the company’s potential. Additionally, the integration of more macro-sensitive indicators or forward-looking metrics could help the strategy avoid negative selection in unstable sectors.

A key strength of this project has been the combination of theoretical guidance and real-world application. By relying on Bloomberg for data collection and R for portfolio analysis, we were able to backtest and monitor the evolution of our strategy over time. At the same time, using academic research as a guiding framework added consistency to the filter design and reinforced the logic behind every decision made.

In conclusion, this project has demonstrated that a well-structured screening strategy, supported by academic insight and applied with discipline, can beat the market. We achieved the goal of building a concentrated yet diversified portfolio that performs strongly not only in bull markets but also in recession times. More importantly, we confirmed that value, profitability, and momentum, when applied in a clear sequence, remain powerful tools for equity selection. The work opens up future opportunities for refining the model even further, but the results already show that we are on the right path.

7. Use of AI Tools Declaration

Por la presente, yo, Carlota Gil Higuera, estudiante de Derecho y Business Analytics (E-3 Analytics) de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado titulado "Equity Screening Criteria to Create a Properly Diversified Portfolio", declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación:

1. Brainstorming de ideas de investigación: Utilizado para idear y esbozar posibles áreas de investigación.
2. Crítico: Para encontrar contra-argumentos a una tesis específica que pretendo defender.
3. Referencias: Usado conjuntamente con otras herramientas, como Science, para identificar referencias preliminares que luego he contrastado y validado.
4. Interpretador de código: Para realizar análisis de datos preliminares.
5. Corrector de estilo literario y de lenguaje: Para mejorar la calidad lingüística y estilística del texto.
6. Sintetizador y divulgador de libros complicados: Para resumir y comprender literatura compleja.
7. Revisor: Para recibir sugerencias sobre cómo mejorar y perfeccionar el trabajo con diferentes niveles de exigencia.
8. Traductor: Para traducir textos de un lenguaje a otro.

Afirmo que toda la información y contenido presentados en este trabajo son producto de mi investigación y esfuerzo individual, excepto donde se ha indicado lo contrario y se han dado los créditos correspondientes (he incluido las referencias adecuadas en el TFG y he explicitado para que se ha usado ChatGPT u otras herramientas similares). Soy consciente de las implicaciones académicas y éticas de presentar un trabajo no original y acepto las consecuencias de cualquier violación a esta declaración.

Fecha: 9 de abril de 2025

Firma:

8. Bibliography

Adamiec, L., et al. (2019). Optimal number of assets for reduction of market risk through diversification. *International Journal of Economics, Business and Management Research, 3*(03).

Altman, E. I. (1968). *Financial ratios, discriminant analysis and the prediction of corporate bankruptcy*. The Journal of Finance, 23(4), 589-609.

Alpha Architect. (2024). *Equally Weighted Portfolios: Pros and Cons*. Retrieved from https://alphaarchitect.com/equally-weighted-portfolios/

Asness, C. S., et al. (2013). Value and momentum everywhere. The Journal of Finance, 68(3), 929-985.

Bermejo Climent, R. (2021). *Tesis doctoral: Integración de medidas contables, bursátiles y macroeconómicas para la predicción de retornos anormales en carteras de renta variable mediante el análisis fundamental*. Universidad CEU San Pablo.

Bianchi, D., De Polis, A., & Petrella, I. (2022). *"Taming Momentum Crashes."* SSRN Electronic Journal.

Buffett, W. (1960). *Buffett partnership letters*. Retrieved from: https://www.berkshirehathaway.com/letters/letters.html

Campbell, J. et al. (2022). *Idiosyncratic Equity Risk Two Decades Later* (NBER Working Paper No. 29916). National Bureau of Economic Research. https://doi.org/10.3386/w29916

Chen, H. et al. (2012). Empirical Investigation of an Equity Pairs Trading Strategy. *SSRN Electronic Journal*. [online] doi:https://doi.org/10.2139/ssrn.1361293.

Cirulli, A., & Walker, P. (2024). Outperforming Equal Weighting. *University of Zurich Working Paper*.

Davies, B. L. (2023). *Comparing Equal- and Value-Weighted Portfolios*. Retrieved from https://bldavies.com/blog/comparing-equal-value-weighted-portfolios/

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2011). Predicting material accounting misstatements. *Contemporary Accounting Research*, *28*(1), 17-82. https://doi.org/10.1111/j.1911-3846.2010.01041.x

DeMiguel, V., et al. (2016). Optimal Versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy? *The Review of Financial Studies*, 22(5), 1915–1953.

Eccles, A., et al. (2021). Peak diversification: How many stocks best diversify an equity portfolio? *CFA Institute Enterprising Investor*. Retrieved from: https://blogs.cfainstitute.org/investor/2021/05/06/peak-diversification-how-many-stocks-best-diversify-an-equity-portfolio/.

Elton, E. J., & Gruber, M. J. (1977). Risk reduction and portfolio size: An analytical solution. *The Journal of Business*, *50*(4), 415-437.

Eisfeldt, A., et al. (2022). *"Intangible Value."* Critical Finance Review 11(2): 299-332.

Evans, J. L., & Archer, S. H. (1968). "Diversification and the Reduction of Dispersion: An Empirical Analysis." *The Journal of Finance*, 23(5), 761-767.

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

Fama, E. F., & French, K. R. (1992). *The cross-section of expected stock returns*. *The Journal of Finance*, 47(2), 427–465.

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

Fama, E. F., & French, K. R. (2015). *A Five-Factor Asset Pricing Model*. Journal of Financial Economics, 116(1), 1–22.

Fisher, K. L. (2007). *Super stocks*. McGraw-Hill.

Graham, B. (1949). *The intelligent investor, (re-issue of original 1949 edition)*, Collins 2005. New York.

Greenblatt, J. (2010). *The little book that still beats the market*. Hoboken, N.J.: Wiley, Chichester.

Hyde, C. E. (2014). *An emerging markets analysis of the Piotroski F-Score*. JASSA: The Finsia Journal of Applied Finance, (2), 23–28.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48 (1), 65-91.

Larsen, J. L. (2022). *"Enhanced Portfolio Optimization of Factor Investment Strategies: An Application to Value Investing."* SSRN Working Paper.

Li, C. (2022). *Empirical study on portfolio size and risk diversification: Take stock market in China as example.* Atlantis Press, 648, 2941–2947.

Liu, Y., & Zhu, Y. (2023). Good idiosyncratic volatility, bad idiosyncratic volatility, and the cross-section of stock returns. *Journal of Banking & Finance, 170*, 107343.

Lo, A.W. (2004). *The Adaptive Markets Hypothesis Market Efficiency from an Evolutionary Perspective.* The Journal of Portfolio Management, 30, 15-29.

Malkiel, B. G. (2020). *Un paseo aleatorio por Wall Street: La estrategia para invertir con éxito*. Alianza Editorial.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77-91.

Newbould, G. D., & Poon, P. S. (1993). The minimum number of stocks needed for diversification. *Financial Practice and Education*, *3*(2), 85-87.

Niessen-Ruenzi, A., Ruenzi, S., et al. (2018). *"Corporate Fraud Risk and Stock Market Performance".*

Novy-Marx, R. (2013). The quality dimension of value investing. Rnm. simon. rochester. edu, 1-54.

Pedersen, L. H., Babu, A., & Levine, A. (2021). Enhanced Portfolio Optimization. *Financial Analysts Journal*, *77*(2), 124–151. https://doi.org/10.1080/0015198X.2020.1854543

Piotroski, J. D. (2000). Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers. *Journal of Accounting Research*, *38*, 1-41. https://doi.org/10.2307/2672906

Plyakha, Y., et al. (2014). Equal or Value Weighting? Implications for Asset-Pricing Tests. *Journal of Financial Economics*, 112(1), 25–45.

Qin, N., & Singal, V. (2021). Equal-weighting and value-weighting: Which one is better? *Review of Quantitative Finance and Accounting*, 58, 743–768.

Ren, Y., Tang, G., Li, X., & Chen, X. (2023). *"A Study of Multifactor Quantitative Stock-Selection Strategies Incorporating Knockoff and Elastic Net-Logistic Regression."* Mathematics, 11(16): 3502.

Reschenhofer, C. (2023). *Combining factors*. SSRN.

Ross, S. A., et al. (2017). *Corporate finance: Core principles and applications* (5th ed.). McGraw-Hill Education.

Sahm, C. R. (2019). Direct Stimulus Payments to Individuals. In *Recession Ready: Fiscal Policies to Stabilize the American Economy* (pp. 33–62). The Hamilton Project – Brookings Institution.

Sharpe, W. F. (1964). *Capital asset prices: A theory of market equilibrium under conditions of risk*. *The Journal of Finance*, 19(3), 425–442. https://doi.org/10.2307/2977928

Shiller, R. J. (1981). *Do stock prices move too much to be justified by subsequent changes in dividends?* The American Economic Review, 71(3), 421–436.

Shiller, R. J. (2003). *From efficient markets theory to behavioral finance*. *Journal of Economic Perspectives*, 17(1), 83–104.

Statman, M. (1987). How many stocks make a diversified portfolio? *The Journal of Financial and Quantitative Analysis*, *22*(3), 353-363.

Van Vliet, P., & Blitz, D. (2018). *The Conservative Formula: Quantitative investing made easy*. SSRN.

Vestre, O., & Wikheim, M. (2022). *The Magic Formula: An empirical study on the Oslo Stock Exchange*(Master's thesis). BI Norwegian Business School.

Zaimovic, A., et al. (2021). *How many stocks are sufficient for equity portfolio diversification? A review of the literature*. *Journal of Risk and Financial Management, 14*(11), 551. https://doi.org/10.3390/jrfm14110551

9. Appendix: R Code

```
#------------------------PORTFOLIO SCREENING
ANALYSIS----------------------------

#0. Libraries and installations
------------------------------------------------
rm(list = ls())

#install.packages("readxl")  # Only once!!
library(readxl)


#1. Read Excel
-----------------------------------------------------------------
data <- read_excel("EQBT vs SP500.xlsx", sheet = "Overview")


#2. New Columns
----------------------------------------------------------------
colnames(data) <- c("Date", "EQBT_Return", "EQBT_Turnover",
"SP500_Return")

data$EQBT_Return_decimal <- data$EQBT_Return / 100
data$SP500_Return_decimal <- data$SP500_Return / 100

data$EQBT_Cumulative <- cumprod(1 + data$EQBT_Return_decimal) - 1
data$SP500_Cumulative <- cumprod(1 + data$SP500_Return_decimal) - 1

data$Date <- as.Date(data$Date, format = "%m/%d/%Y")


#3. Plots
----------------------------------------------------------------------

#Plot 1 Cumulative Return
------------------------------------------------------
par(mar = c(5, 5, 4, 6), xaxs = "i")
plot(data$Date, data$EQBT_Cumulative,
     type = "l",
     col = "blue",
     lwd = 2,
     ylab = "Cumulative Return",
     xlab = "Date",
     main = "Cumulative Return: EQBT Portfolio vs S&P 500",
     cex.main = 1.2,
     cex.lab = 1,
     cex.axis = 0.9)

lines(data$Date, data$SP500_Cumulative, col = "red", lwd = 2)

legend("topleft",
       legend = c("EQBT Portfolio", "S&P 500"),
       col = c("blue", "red"),
       lwd = 2,
       cex = 0.8,
       bty = "n")
```

```
last_x <- tail(data$Date, 1)
last_y_eqbt <- tail(data$EQBT_Cumulative, 1)
last_y_sp <- tail(data$SP500_Cumulative, 1)

text(x = last_x,
     y = last_y_eqbt,
     labels = paste0(round(last_y_eqbt * 100, 2), "%"),
     pos = 2, col = "blue", cex = 0.9, offset = 0.5)

text(x = last_x,
     y = last_y_sp,
     labels = paste0(round(last_y_sp * 100, 2), "%"),
     pos = 2, col = "red", cex = 0.9, offset = 0.5)


#Plot 2 Cumulative Spread
------------------------------------------------------
data$Cumulative_Spread <- data$EQBT_Cumulative - data$SP500_Cumulative

par(mar = c(5, 5, 4, 2), xaxs = "i")

plot(data$Date, data$Cumulative_Spread,
     type = "l",
     col = "darkgreen",
     lwd = 2,
     ylab = "Cumulative Spread",
     xlab = "Date",
     main = "Cumulative Return Spread: EQBT vs S&P 500",
     cex.main = 1.2,
     cex.lab = 1,
     cex.axis = 0.9)

abline(h = 0, col = "gray", lty = 2)

polygon(
  x = c(data$Date, rev(data$Date)),
  y = c(rep(0, length(data$Cumulative_Spread)),
rev(data$Cumulative_Spread)),
  col = adjustcolor("green", alpha.f = 0.3),
  border = NA
)

last_x <- tail(data$Date, 1)
last_y <- tail(data$Cumulative_Spread, 1)

text(x = last_x,
     y = last_y,
     labels = paste0(round(last_y * 100, 2), "%"),
     pos = 2, col = "darkgreen", cex = 0.9, offset = 0.5)
```

```
#----------------------PORTFOLIO SCREENING
ANALYSIS----------------------------

#0. Libraries and installations
------------------------------------------------
rm(list = ls())

#install.packages("readxl")
library(readxl)

#1. Read and prepare the data
--------------------------------------------------
counts <- read_excel("EQBT vs SP500.xlsx", sheet = "Counts", skip = 2)

colnames(counts) <- c("Date", "In", "Same", "New", "Dropped", "Turnover")

counts$Date <- as.Date(counts$Date, format = "%m/%d/%y")


#2. Number of Stock in each Rebalancing Period
---------------------------------

counts$Positive_Stack <- counts$Same + counts$New
counts$Negative_Stack <- -counts$Dropped

x_vals <- as.numeric(counts$Date)
bar_width <- 70

ylim_max <- max(counts$Positive_Stack, na.rm = TRUE) + 5
ylim_min <- min(counts$Negative_Stack, na.rm = TRUE) - 5

plot(x_vals, counts$Positive_Stack,
     type = "n",
     xaxt = "n",
     ylim = c(ylim_min, ylim_max),
     xlab = "Date",
     ylab = "Number of Stocks",
     main = "Portfolio Composition per Rebalancing")

rect(x_vals - bar_width, 0, x_vals, counts$Same, col = "skyblue", border =
NA)
rect(x_vals - bar_width, counts$Same, x_vals, counts$Same + counts$New,
col = "light green", border = NA)

rect(x_vals - bar_width, 0, x_vals, counts$Negative_Stack, col = "dark
red", border = NA)

years <- format(counts$Date, "%Y")
quarters <- format(counts$Date, "%m")
is_last_quarter <- quarters == "12"
year_labels <- ifelse(is_last_quarter, years, "")  # Show year only in Q4

axis(1, at = x_vals, labels = year_labels, las = 2, cex.axis = 0.7)

legend("topright",
       legend = c("Stayed", "New", "Dropped"),
       fill = c("skyblue", "light green", "dark red"),
```

```
       border = NA,
       cex = 0.8,
       bty = "n")

mean_in <- mean(counts$In, na.rm = TRUE)

abline(h = mean_in, col = "black", lty = 2)

axis(2, at = mean_in, labels = paste(round(mean_in, 1)), las = 0, tick =
TRUE, line = 0, col.axis = "black", cex.axis = 1)
```

```
#------------------------PORTFOLIO SCREENING
ANALYSIS----------------------------

#0. Libraries and installations
------------------------------------------------
rm(list = ls())

#install.packages("readxl")
# 1. Load library
library(readxl)

# 2. Read the Excel file and skip the first 3 rows
data <- read_excel("Total Return Vs ETF.xlsx", sheet = "Total Return",
skip = 3)

# 3. Columns and dates
colnames(data) <- c("Day_of_Week", "Date", "EQBT_Cumulative",
"ETF_Cumulative")

data$Date <- as.Date(data$Date, format = "%m/%d/%y")

# 4.Cumulative Returns
data$EQBT_Cumulative <- as.numeric(data$EQBT_Cumulative)
data$ETF_Cumulative <- as.numeric(data$ETF_Cumulative)

par(mar = c(5, 5, 4, 6), xaxs = "i")
plot(data$Date, data$EQBT_Cumulative,
     type = "l",
     col = "blue",
     lwd = 2,
     ylab = "Cumulative Return",
     xlab = "Date",
     main = "Cumulative Return: EQBT Portfolio vs ETF",
     cex.main = 1.2,
     cex.lab = 1,
     cex.axis = 0.9)

lines(data$Date, data$ETF_Cumulative, col = "red", lwd = 2)
legend("topleft",
       legend = c("EQBT Portfolio", "ETF"),
       col = c("blue", "red"),
       lwd = 2,
       cex = 0.8,
       bty = "n")


last_x <- tail(data$Date, 1)
last_y_eqbt <- tail(data$EQBT_Cumulative, 1)
last_y_etf <- tail(data$ETF_Cumulative, 1)


text(x = last_x, y = last_y_eqbt,
     labels = paste0(round(last_y_eqbt, 2), "%"),
     pos = 2, col = "blue", cex = 0.9, offset = 0.5)

text(x = last_x, y = last_y_etf,
     labels = paste0(round(last_y_etf, 2), "%"),
     pos = 2, col = "red", cex = 0.9, offset = 0.5)
```

```r
#5. Spread

data$Spread <- data$EQBT_Cumulative - data$ETF_Cumulative

par(mar = c(5, 5, 4, 2), xaxs = "i")
plot(data$Date, data$Spread,
     type = "l",
     col = "darkgreen",
     lwd = 2,
     ylab = "Cumulative Spread (%)",
     xlab = "Date",
     main = "Cumulative Return Spread: EQBT vs ETF",
     cex.main = 1.2,
     cex.lab = 1,
     cex.axis = 0.9)


abline(h = 0, col = "gray", lty = 2)

polygon(
  x = c(data$Date, rev(data$Date)),
  y = c(rep(0, length(data$Spread)), rev(data$Spread)),
  col = adjustcolor("green", alpha.f = 0.3),
  border = NA
)

last_x <- tail(data$Date, 1)
last_y <- tail(data$Spread, 1)

text(x = last_x,
     y = last_y,
     labels = paste0(round(last_y, 2), "%"),
     pos = 2, col = "darkgreen", cex = 0.9, offset = 0.5)
```

```
#------------------------------REGLA DE
SAHM---------------------------------

#0. Libraries and installations
---------------------------------------------
rm(list = ls())

#install.packages("readxl")
# 1. Load library
library(readxl)

#1. Read Excels
-------------------------------------------------------------
data <- read_excel("EQBT vs SP500.xlsx", sheet = "Overview")
sahm<-read_xlsx("Regla de Sahm.xlsx")

#2. New Columns
------------------------------------------------------------
colnames(data) <- c("Date", "EQBT_Return", "EQBT_Turnover",
"SP500_Return")
colnames(sahm)<-c("Date", "Value")


#3. Handle Dates
-----------------------------------------------------------
data$Date <- as.Date(data$Date, format = "%m/%d/%Y")
sahm$Date<-as.Date(sahm$Date)

#4. Inner Join
-------------------------------------------------------------
merged<-inner_join(data, sahm, by="Date")

#5. Recession indicator
-----------------------------------------------------
merged$Recession<-ifelse(merged$Value>0.5, 1, 0)

#6. Plot
-------------------------------------------------------------------

shade_data <- merged %>%
  filter(Value > 0.5) %>%
  mutate(xmin = Date,
         xmax = Date + 90)  # sombrear un trimestre aprox.

library(ggplot2)

ggplot(merged, aes(x = Date)) +
  geom_rect(data = shade_data,
            aes(xmin = xmin, xmax = xmax, ymin = -Inf, ymax = Inf),
            fill = "red", alpha = 0.1, inherit.aes = FALSE) +

  geom_line(aes(y = EQBT_Return, color = "Portfolio Return"), size = 1) +
  geom_line(aes(y = Value * 10, color = "Sahm Rule"), linetype = "dashed",
size = 1) +
  scale_y_continuous(
    name = "Portfolio Return",
    sec.axis = sec_axis(~ . / 10, name = "Sahm Rule")
  ) +
```

```
  scale_color_manual(values = c("Portfolio Return" = "blue", "Sahm Rule" =
"orange")) +
  labs(title = "Portfolio Return and Sahm Rule",
       x = "Date",
       color = " ") +
  theme_minimal() +
  theme(
    legend.position = "top",
    legend.text= element_text(size=12),
    panel.grid = element_blank())

#7. Summarise
library(dplyr)

merged %>%
  group_by(Recession) %>%
  summarise(
    Mean_EQBT_Return = mean(EQBT_Return, na.rm = TRUE),
    Vol_EQBT_Return  = sd(EQBT_Return, na.rm = TRUE),

    Mean_SP500_Return  = mean(SP500_Return, na.rm = TRUE),
    Vol_SP500_Return   = sd(SP500_Return, na.rm = TRUE),

    Sharpe_EQBT = Mean_EQBT_Return / Vol_EQBT_Return,
    Sharpe_SP500 = Mean_SP500_Return / Vol_SP500_Return,

    n = n()
  )
```

```
#--------------------------------SHARPE
RATIO-----------------------------------

#0. Libraries and installations
------------------------------------------------
rm(list = ls())

#install.packages("readxl")  # Only once!!
# Load libraries
library(readxl)
library(dplyr)
library(tidyr)
library(lubridate)
library(ggplot2)


#1. Read Excels
----------------------------------------------------------------
sectors<-read_excel("Sectors.xlsx")
total<-sectors[1,]
sectors<-sectors[-c(1,11,12),]


#2. New Columns
----------------------------------------------------------------
colnames(sectors)=c("Sector", "Port_Avg_Weight", "Bench_Avg_Weight",
"Diff_Avg_Weight",
                   "Port_Tot_Return", "Bench_Tot_Return",
"Diff_Tot_Return",
                   "Port_Contrib", "Bench_Contrib", "Diff_Contrib",
                   "Allocation", "Selection", "Currency", "Alpha")
colnames(total)=c("Sector", "Port_Avg_Weight", "Bench_Avg_Weight",
"Diff_Avg_Weight",
                    "Port_Tot_Return", "Bench_Tot_Return",
"Diff_Tot_Return",
                    "Port_Contrib", "Bench_Contrib", "Diff_Contrib",
                    "Allocation", "Selection", "Currency", "Alpha")

sectors$Sector<-gsub(" ", "\n", sectors$Sector)


#3. Contribution to Return per Sector (%)
--------------------------------------
ggplot(sectors, aes(x=reorder(Sector, Port_Contrib), y=Port_Contrib)) +
  geom_col(fill="steelblue") +
  geom_text(aes(label=round(sectors$Port_Contrib)), vjust=-0.5, size=5.5,
color= "darkgrey",fontface="bold") +
  labs(title="Contribution to Total Return by Sector",
       x=" ", y="Contribution (%)") +
  theme_minimal() +
  theme(
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    axis.text.x=element_text(size=14),
    axis.text.y=element_text(size=14)
  )
```

```
#4. Alpha-Weight and Contribution to Total Return
ggplot(sectors, aes(x = Port_Avg_Weight,
                    y = Alpha,
                    size = Port_Contrib,
                    label = Sector)) +
  geom_point(color = "steelblue", alpha = 0.8) +  # todas las burbujas en
azul
  geom_text(aes(label = ifelse(Port_Contrib > 20, Sector, "")),  # solo
etiquetas relevantes
            color = "black",
            size = 4,
            vjust = -0.5) +
  scale_size_continuous(name = "Contribution to Total Return", range =
c(3, 20)) +
  labs(title = "Alpha vs Portfolio Weight",
       x = "Portfolio Weight (%)",
       y = "Alpha (%)") +
  theme_minimal()


#5. Selection vs Allocation

sectors <- sectors %>%
  arrange(Alpha) %>%
  mutate(Sector = factor(Sector, levels = Sector))

df_long <- sectors %>%
  select(Sector, Allocation, Selection, Alpha) %>%
  pivot_longer(cols = c("Allocation", "Selection"),
               names_to = "Effect", values_to = "Value")


ggplot(df_long, aes(x = Sector, y = Value, fill = Effect)) +
  geom_col() +

  geom_point(data = sectors,
             aes(x = Sector, y = Alpha),
             color = "black", size = 2,
             inherit.aes = FALSE) +  # ← IMPORTANTE

  geom_line(data = sectors,
            aes(x = Sector, y = Alpha, group = 1),
            color = "black", linetype = "dashed",
            inherit.aes = FALSE) +  # ← IMPORTANTE

  labs(title = "Alpha Breakdown: Allocation + Selection Effects",
       subtitle = "Black dashed line = Total Alpha per sector",
       x = "Sector", y = "Effect (%)",
       fill=" ")+
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size=13),
        legend.position = "top"
  )
```