DEPARTMENT OF MATHEMATICS

CATARINA AVELINO PALMA RAMOS

BSc in Matemática Aplicada à Gestão do Risco

# TOOL-ASSISTED VALIDATION OF FACTOR-BASED INVESTMENT STRATEGIES

## WITHIN THE SCOPE OF THE EUROPEAN MARKET

MASTER IN MATEMÁTICA E APLICAÇÕES COM ESPECIALIZAÇÃO EM MATEMÁTICA FINANCEIRA

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**Tool-assisted Validation of Factor-based Investment Strategies**
**within the scope of the European Market**



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# Abstract

This thesis is aimed towards the implementation, analysis and fusion of various factor-based investment strategies on the biggest European market. We were focused on studying a contrarian investment strategy, two value investment strategies, and a momentum strategy. These four different methodologies of stock selection were put to the test during the period 2015-2019 on this market and their merging provides a rich sense of how well these factors can work together. For this purpose, we utilized the Python framework Qrumble, for quick and straight-forward results of investments experiments. To accomplish such thorough analysis, we incorporated into Qrumble more portfolio evaluation metrics and two theoretically efficient portfolios from Portfolio Theory, the minimum variance portfolio and market portfolio. We found that most investment strategies didn't succeed as expected, probably due to the limited period of experiment. On the other hand, both value strategies revealed interesting returns without much higher risk involved. Finally, we achieved better results through a multi-type factor investment strategy by combining factors from said strategies, which can be a sign that these different schools of thought can collaborate effectively. This also exhibited that theoretically efficient portfolios can have interesting outcomes within the right circumstances, which requires future work.

**Keywords:** Factor-based Investing, Portfolio Theory, Efficient Portfolio, Decision Support System

# Resumo

Esta dissertação visa a implementação, análise e fusão de diversas estratégias de investimento baseadas em fatores no maior mercado europeu. O nosso objetivo foi estudar uma estratégia de investimento contrariana, duas estratégias de investimento de valor e uma estratégia momentum. Estas quatro metodologias diferentes de seleção de ações foram avaliadas durante o período de 2015-2019 e a sua junção fornece uma perspetiva enriquecida de como estes fatores podem funcionar em conjunto. Para isto, utilizámos a estrutura em Python Qrumble, para obter resultados diretos e simples das experiências de investimento. Para realizar uma análise completa, incorporámos no Qrumble mais métricas de avaliação de carteiras e duas carteiras teoricamente eficientes da Teoria de Carteira, as de variância mínima e de mercado. Verificámos que a maioria das estratégias de investimento não tiveram o sucesso esperado, provavelmente devido ao período limitado da experiência. Já as estratégias de valor revelaram retornos interessantes sem um risco muito maior. Por último, obtivemos melhores resultados através de uma estratégia de investimento combinando alguns fatores das referidas estratégias, o que pode indicar que estas diferentes vertentes podem colaborar eficazmente. Isto também implicou que carteiras teoricamente eficientes podem ter resultados interessantes nas circunstâncias certas, o que requer trabalho futuro.

**Palavras-chave:** Investimento com base em Fatores, Teoria de Carteira, Carteira Eficiente, Sistema de Apoio à Decisão

# Contents

# List of Figures

# List of Tables

# List of Listings

Chapter 1

# Introduction

## 1.1 Motivation

It's essential to know how to qualify and grade companies and businesses and to forecast price movements, since the investments surrounding them move the world around, money-wise. Although there's no key rule on how to say what's best or what it isn't, the best we can do is look for strategies already studied in this field as a first step. This section is focused on understanding the purpose of these strategies, i.e. who is this dedicated to.

It is well known that money loses its value eventually, so the simple solution for most is to move it, in various ways. The main sectors occupied with this issue are banks, insurers, big (mostly international) firms, brokers, celebrities and wealthy individuals, and self-proclaimed investors, to name a few. Simply put, a bank's primary function is guarding the money of its clients, but how does it not "lose" it and even make a profit from it? It can lend the money received from its clients to other clients or firms with interest incorporated in that contract, obtaining it all back and a fraction more, which we call as a margin of profit. Besides this, banks also invest in financial products with a rate of returns larger than what they're going to pay back to their depositors. Insurers work similarly, although their purpose is to manage money from clients' premiums for pensions, insurance, and compensations. In this sense, they also need to know the best investment strategies to restabilize the premium they receive from their clients. Of course, this activity involves risk, so the bank or insurers also need to have an idea of the credibility of the client and that's where "quality control" strategies can take place.

Furthermore, with the rise of data analytics and processing, financial tools are consistently growing, delivering historical and real-time insights into the economy and capital markets. This quantity of data opens opportunities to improve stock selection based on past historical price oscillations.

Throughout history, investment experts and individuals alike have become passionate about studying and elaborating investment strategies based on a wide range of information and indicators, to maximize their wealth. The same goes, at a larger scale, for banks, insurers and other financial institutions. However, this task is not as straightforward as solving a maximization problem. It requires a deep understanding of the origin of various factors, their significance, and their impact on the companies' performances in different markets. In the end, it's a game of trust and each investor considers the indicators they believe are the most relevant, according to their own risk aversion.

> "In addition to historically exhibiting excess returns above the market, an equally important rationale for factor investing is the wealth of evidence that they can account for a significant portion of mutual fund returns and institutional active fund returns" (Bender et al., 2013).

## 1.2 Objectives and Contributions

This thesis has as its main objective the study and understanding of popular investment strategies developed by Financial Mathematics and Economics experts, according to their own interests, theories and purposes. Two of the investment strategies considered are from the sector of value investing, F_score (Piotroski, 2000) and Magic Formula (Greenblatt, 2006). The other two include a contrarian strategy, Dogs of the Dow (O'Higgins & Downes, 2010) and a momentum strategy, Buying Winners and Selling Losers (Jegadeesh & Titman, 1993).

Another important goal consists of the validation of Qrumble, a decision support system in the experimentation process of investment strategies (Santos, 2023). Qrumble is optimised to show the effects and outcomes of investment strategies in a straightforward and effective way, with recent data and available factors in hand. Like so, examining the capabilities of Qrumble in the context of evaluating investment strategies, with a range of metrics and weight schemes emerges as a purpose and a contribution. This framework directs us to the application of these strategies on the biggest European market, the STOXX600, from 2015 to 2019, as another objective.

As for the analysis of said strategies, the goal also extends to implementing some theoretical concepts of Portfolio Theory, by including more portfolio evaluation measures, such as beta, alpha, Value at Risk and Tail Value at Risk, and also experimenting those strategies in two other types of portfolios designed to be efficient, at least in theory. Therefore, in addition to analysing investment strategies in typical real-world portfolios, we have added the minimum variance portfolio and market portfolio, which, under less specific and broader conditions, are designed to generate the maximum return taking into account a specific risk. The aim of this contribution is to see if it is possible to achieve results with less risk and/or more return within the same selection of stocks on different weight schemes than the portfolios we are used to seeing employed all the time.

In support of this, there were some additional contributions. We executed comparative studies between the results of the different investment strategies and fusions of various factors with the purpose of comprehending how well multi-type factors conjugate with each other. Furthermore, sensitivity analyses were applied and we were focused on studying how various metrics behave depending on the strategy.

With all this, we hope contribute to the body of knowledge of how to pick interesting stocks with a range of factors in mind.

## 1.3 Thesis Structure

The work is organized as follows. **Chapter 1** is focused on introducing the theme of the thesis, with motivation, objectives and contributions. **Chapter 2** represents a summarised literature review of Portfolio Theory and factor investing routes. **Chapter 3** presents financial mathematics notions and theories for efficient portfolios and risk measurement. **Chapter 4** consists of in-depth explanation of each investment strategy. **Chapter 5** is directed torwards describing and interpreting Qrumble. **Chapter 6** displays the results of the investment strategies experiences and its discussions, analyses and comparisons. Finally, **Chapter 7** conducts the conclusion and suggestions for future work.

Chapter 2

# Literature Review

Throughout the growth of commerce, businesses, and contracts in Europe, Rae (1834) contributed immensely to the need for comprehending the purpose and functionality of financial markets with his theory of capital in "New Principles on the Subject of Political Economy", based on consumer preferences and production. This theory was later applied in a systematic mathematical mindset by Fisher (1930). This work was critical for the idea of equilibrium in financial markets with consumer preferences without uncertainty and under the assumption that agents can predict interest rates' movements.

A few years later, there were some progresses not based on the analysis of the security market's equilibrium, by Graham and Dodd (1934) and Williams (1938), but achieving substantial advancements surpassing Fisher's academic work required mathematically modelling the income streams of a limited number of securities as random variables.

There was the probability theory approach by Arrow (1953), where the income streams behave like functions defined on states of nature and it contributed to the general equilibrium model with financial markets. Yet, Markowitz (1952) took the statistical theory approach and treated the income streams by distribution moments, which inspired the Capital Asset Pricing Model. These two papers became the pioneers of the modern theory of finance. Diversification was one of the key concepts brought by Markowitz. He found that the security analysis created by Graham and Dodd (1934) was so focused on maximizing the portfolio's expected returns, that ignored the high risks of chosen portfolios only with the security corresponding to the highest expected return. Diversification of the portfolio proved to be the solution to this challenge, as it diminishes the variability of portfolio returns to a point of being arbitrarily small, over a sufficiently large number of independent risks. Accordingly, Markowitz (1952) crafted a way to discover efficient portfolios that would satisfy risk-averse investors, by finding the portfolio with the lowest possible variance for a given expected return.

Influenced by the previous work, Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966) were determined in reaching the equilibrium of financial markets with the Capital Asset Pricing Model (CAPM), assuming that all investors have mean-variance preferences.

> "The basic message of the CAPM model that diversification reduces risk and that the risk which influences the price of a security is the volatility of its return relative to some appropriate index (or family of indices) has had a lasting impact not only on the finance literature but also on the thinking that guides the investment policies of professionals in major financial centres, those who manage the portfolios of pension funds, mutual funds, banks and corporations" (Magill & Quinzii, 1996).

The CAPM also proposed that portfolio return is proportionally sensitive to market risk, being the latter the only risk considered for any reward. Subsequently, Ross (1976) created the Arbitrage Pricing Theory (APT), which takes into account multiple types of (systematic) risk, despite having no specification on which risks should lead to compensation. Like so, "the expected return of a financial asset can be modelled as a function of various macroeconomic factors or theoretical market indexes" (Bender et al., 2013). With the popularization of the term factor, the APT turned out to be the basis of multi factor-based investing.

Two decades after the 70's, with the rise of the Efficient Market Hypothesis (Fama, 1970), the general accepted idea was that news and information were quickly translated into security prices and markets were efficient by nature. Therefore, there was no need or motivation to apply fundamental analysis (study of public information and financial statements) nor technical analysis (study of past stock prices to predict future ones) to generate higher returns. However, that was changed with the studies, rationale and criticism by value investors, behavioural finance academics and technical implementations on investments. For example, some contrarian anomalies through fundamental analysis came to light with empirical research. In Basu's (1977) research, stock characteristics seemed to be influential on stock returns. Another anomaly came with Banz (1981) who evidenced that small market capitalization stocks in portfolios experience higher risk-adjusted returns than portfolios with assets characterized by large market capitalization (see Pappas and Dickson (2015)). Later, these anomalies were associated with a low book-to-market value at the time.

In the value investment approach, the market is unpredictable and unstable in the short term, but profitable in the long term taking the quantitative factors of businesses present on their income statements (fundamental factors) into account. As the father of value investing pointed out, the market is a "voting mechanism" in the short term, and a "weighting mechanism" in the long one (Graham, 1965). Value investing is an approach to help with the allocation of capital based on fundamental factors. This originated with the idea of comparing price and intrinsic value of an asset, since this value is a volatile measure of a company's valuation and not always equal to its value represented in the market (market value). This fluctuation is the baseline of finding and investing in undervalued businesses, i.e. when the share price is lower than its intrinsic value, with the hope that its price value will rise to its true worth in the future. These concepts were first created by Graham and Dodd (1934) and represent the core of value investing. The authors possessed an entrepreneurial school of thought, in a way that crafting an investment revolved around the principles of the business economy would lead to more success. The difference between the price paid and the intrinsic value is called a margin of safety and the higher it is, the better the business performance and less risk involved. In this strategy, they prioritized fundamental factors such as low debt-to-equity ratio and high dividend yields. Fama and French (1992) were inspired by the classification of value companies and found that firms with low market capitalization and a lower price to book value have better returns than the contrary. In the midst of understanding the origin of premium value, they associated it as a risk compensation hypothesis. The three-factor model is then created (Fama & French, 1993) with market excess return, book-to-market factor (high-minus-low book-to-market) and company size effect (small-minus-big). This expansion of the CAPM with size risk and value risk factors proved to be successful. Also inspired by Graham and Dodd (1934), Lakonishok et al. (1994) demonstrated that the exploitation of the sub optimal behavior of the common investor within the value strategy is what generates higher returns, instead of being a premium for risk. In favor of the value approach, value stocks are undervalued in relation to their fundamental signals, due to behavioral weaknesses and judgemental biases of investors and they can be taken advantage of for more elevated long-term results. Overestimation of future growth rates can extrapolate the past fundamental too far into the future. The results are also explained by the spotlight being in growth stocks with a shorter-term high growth potential, leaving value strategies avoided, less exhausted, cheaper and with a higher average return.

There is a resembling investment strategy to value strategy, called contrarian investment strategy, as it recognizes unpopular companies or organizations and tries to sell their assets for cheaper due to the rebound, but takes into consideration the psychological reasoning of the market's behaviour. Contrarian strategies were first created by De Bondt and Thaler (1985) and are rooted on the overreaction hypothesis, where investors react excessively to information, increasing stock price oscillations. If the oscillation turned out to be positive, then investors would be overly optimistic, leading to overpriced assets, while the opposite would occurr alongside with excessive pessimism if price movements were negative. This phenomenon was later associated with representativeness bias, stated by Barberis et al. (1998), where businesses with good results are viewed as a representative of a good business, which investors will trust their capital on the most. This induces extreme mispricing and overconfidence. The overreaction hypothesis anticipated this occurrance and expects that the bigger the mispricing error, the bigger its correction (De Bondt & Thaler, 1985). Although value and contrarian investing are analogous, the first one focuses on value ratios while the second can also analyse past returns to help in identifying loser and winner stocks. Like so, contrarians look for out-of-favour and ignored stocks (losers) to buy, and later sell them when they're popular, usually with a long-term horizon in mind, while value investors seek undervalued stocks. This contrarian school of thought is usually riskier because of the uncertainty of profit and the time required to generate that profit (Jagirdar & Gupta, 2023).

Besides this, there was a completely divergent perspective submerging, with the intention of comprehending investors' reaction to new information and profiting from higher returns. In the 70's, financial researchers were certain that stock prices followed a random walk and patterns were just the consequence of data snooping, so past information couldn't estimate future stock prices (Fama, 1970). As previously mentioned above, this faced a lot of criticism from anomalies not only by value investing enthusiasts, but also by momentum investing researchers. Although Levy (1967) introduced the momentum term of "relative strength" first, momentum investing gained its popularity initially by Jegadeesh and Titman (1993), when they demonstrate that equities with higher past returns persist on having superior returns in the future, over the next three to twelve months, and equities with lower past returns tend to worsen their future returns within the next months. In their ideology, buying the past winners and selling the past losers would generate substantial profits. When experimenting with a range of combinations of formation and holding periods, researchers consider that the six months of momentum analysis prior to portfolio formation and a holding period of six months is the best combination. Momentum strategies were then based on the underreaction hypothesis, in the sense that investors don't react much to new information and asset prices fall short on adapting adequately. This strategy of investing relies on short-term analysis and profit for success. Despite the unanimous agreement of the momentum effect between scholars, there is not a consensus on the explanation of momentum investing. For example, rational thinkers state that momentum premium comes as a compensation for elevated risk, and suggest implementations of risk-based momentum models (see Johnson (2002)). There is also another behavioural school of thought, where rational models suffer data mining, and overreaction models assume investors actually overreact to stock prices, which distances them from their intrinsic values, causing short-term momentum (see Adebambo and Yan (2016)), in addition to the theory of underreaction. Apart from these theories, the question whether momentum and value investing could benefit from one another remained, and there were some research studies that reported momentum payoffs alongside fundamentals. Asem (2009) demonstrated enhanced momentum payoffs in taking long positions in stocks that had raised dividends and short assets that had done the opposite, with the underreaction hypothesis in mind. Booth et al. (2016) revealed momentum effect alongside with firm size, where "small-firm effect dominates price momentum in the long run", in support of rational theory.

Chapter 3

# Measures of Risk

## 3.1 Capital Asset Pricing Model

In this section, we present the theory behind the Capital Asset Pricing Model, by following Huang and Litzenberger (1988).

### 3.1.1 Model Framework

Let's consider a financial structure with $n$ securities with expected returns as

$$\begin{bmatrix} E(r_1) \\ E(r_2) \\ \cdots \\ E(r_n) \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \cdots \\ \mu_n \end{bmatrix} = \mu$$

where $r_i = \dfrac{P_{i,t+1} - P_{i,t}}{P_{i,t}}$, $P_{i,t}$ is the price of asset $i$ at time $t$ and $E(r_i)$ is the expected return of asset $i$, with $i = 1, \dots n$.

Let $\sigma_i^2$ denote the variance of return of asset $i$ with $i = 1, \dots n$ and $\sigma_{ij}$ denote the covariance between assets $i$ and $j$, $\; i, j = 1, \dots n$ where $i \neq j$.

We denote by $\Sigma$ the variance-covariance matrix, that is,

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2n} \\ \cdots & & & \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_n^2 \end{bmatrix}$$

Let $w = (w_1, \cdots, w_n)$ be a portfolio of the $n$ assets, with $\sum_{i=1}^{N} w_i = 1$. In other words, $w_i$ is the proportion of wealth invested on asset $i$. The portfolio return is given by the random variable

$$r_p = w_1 r_1 + w_2 r_2 + \cdots + w_n r_n \ .$$

The expected return of the portfolio is portrayed as

$$\begin{aligned} E(r_p) &= w_1 E(r_1) + w_2 E(r_2) + \cdots + w_N E(r_N) = \\ &= w_1 \mu_1 + w_2 \mu_2 + \cdots + w_N \mu_N \\ &= w' \mu \ . \end{aligned}$$

On the other hand, the variance of the portfolio is given by

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1, j \neq i}^{n} w_i w_j \sigma_{i,j} = w' \Sigma w \ .$$

It is important to note that the combined risk of the assets altogether (reflected in the covariance) is crucial for obtaining the risk associated with the portfolio, simply because the portfolio's risk isn't equal to the sum of the risks of its individual assets.

### 3.1.2 Assumptions

As any theoretical model, it possesses some underlying assumptions as a skeleton. Firstly, investors and brokers are primarily risk-averse, namely they prefer the least risk as possible when trying to achieve high returns. Similarly, they also aim to maximize their final wealth utility, in a way that each investor has their own preferences which can be not fixed in return. In this sense, they make their decisions mostly based on return (average of portfolio returns) and risk (variance) and all people have similar expectations and estimates for these metrics. They also have an identical time horizon, i.e. they buy and sell all their equities at non specific but common point in time, having a similar time horizon. Continuing with general considerations, any person interested in seeking investment strategies has free access to the same available information as anybody else, with no cost. Speaking of costs, there are no transaction ones and no taxes. Assets are also totally available for marketability and divisibility, in a way that the number of equities is fixed. Finally, the risk-free asset exists and there is no restriction on lending and borrowing at the risk-free rate. Some, or even all of these assumptions, can be highly unrealistic and extremely difficult to achieve in real life investments.

### 3.1.3 Efficient Frontier with Risky Assets

In the process of selecting a portfolio, there are a variety of elements to consider. In a ideal world, investors would only look for the expected returns of a certain number of assets and make a simple decision about their investment to maximize the overall expected return of the portfolio. However, we know that there are core aspects that get in the way of this ideal and easy plan, such as fees and expenses, investment horizon, market conditions, and, most importantly, risk tolerance. Risk here reflects the variability and uncertainty of the returns of investment since the actual returns can differ from the expected ones.

Markowitz (1952) assumed that the investor has mean-variance preferences, that is, preferences increase with expected return and decrease with risk, which leads to the concept of an efficient portfolio.

**Definition 3.1.1** *An **Efficient Portfolio** is a portfolio with the lowest variance for a given expected return. It can also be defined as the portfolio with the highest expected return for a given variance.*

Let's suppose there are only risky assets. The problem designated to compute efficient portfolios as defined above is the following

$$\min_{(w_1,w_2,\ldots,w_n)} \quad w'\Sigma w \tag{3.1}$$
$$\text{s.t.} \quad w'\mu = \mu_p$$
$$w'\mathbf{1} = 1$$

with $\mathbf{1} = \begin{bmatrix} 1 \\ 1 \\ \cdots \\ 1 \end{bmatrix}$ as a $n$x1 matrix.

For each level of expected return, $\mu_p$, the solution of this problem indicates the composition of the portfolio with the lowest variance. The solution of the problem that can be computed using the Lagrangian method is as follows

$$w_p^* = \frac{C\mu_p - A}{D}\Sigma^{-1}\mu + \frac{B - A\mu_p}{D}\Sigma^{-1}\mathbf{1} \tag{3.2}$$

whereas $A = \mathbf{1}^T\Sigma^{-1}\mu$, $B = \mu'\Sigma^{-1}\mu$, $C = \mathbf{1}^T\Sigma^{-1}\mathbf{1}$ and $D = BC - A^2$.

The geometric region of efficient portfolios in the $(\sigma_p, E(r_p))$-space is given by a hyperbole, see Figure 2.1. The portfolio with the smallest variance is the point in the vertex of the hyperbole and its variance and expected return consist of

$$Var(r_{mvp}) = \frac{1}{C} \text{ and } E(r_{mvp}) = \frac{A}{C}.$$

To find the weights of the minimum variance portfolio, we just have to substitute the $\mu_p$ by $E(r_{mvp})$ in the equation (3.2).

The mean-variance frontier, or efficient frontier, is the geometric location in the $(\sigma_p, E(r_p))$-space of portfolios that solve the minimization problem in (3.1). The efficient frontier is composed of the portfolios in the mean-variance frontier that satisfy $E(r_p) > \frac{A}{C}$.

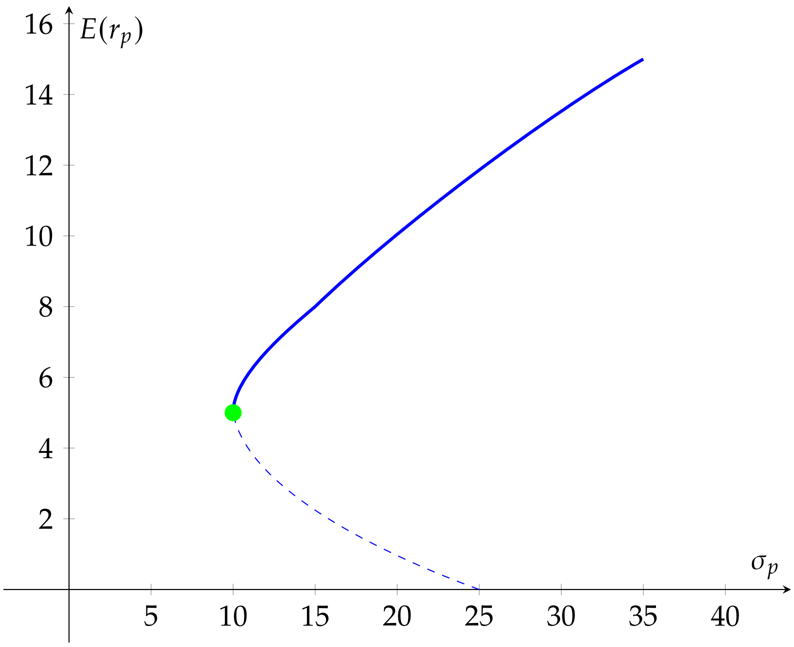


Figure 3.1: Efficient frontier example expressed by top of the hyperbole in blue, containing the minimum variance portfolio in the green dot.

### 3.1.4 Efficient Portfolios with Risky Assets and a Risk-Free Asset

Now, let's suppose there is a risk-free asset, that is, an asset $f$ with $r_f$ as its return and variance $\sigma_f = 0$. Besides this, let's say we have a portfolio $a$ with risky assets, which we can combine with the risk-free asset in a portfolio $p$. The proportions are $(w_a, 1 - w_a)$, respectively. In this way, the return, expected return, and variance are given by

$$r_p = (1 - w_a)r_f + w_a r_a$$

$$E(r_p) = (1 - w_a)r_f + w_a E(r_a) = r_f + w_a\Big(E(r_a) - r_f\Big) \tag{3.3}$$

$$\sigma_p^2 = w_a^2 \sigma_a^2 \iff w_a = \frac{\sigma_p}{\sigma_a} \tag{3.4}$$

By combining the equations (3.3) and (3.4), we obtain the Capital Allocation Line (CAL).

This equation defines a straight line in the $(\sigma_p, E(r_p))$-space which is the geometric region of all portfolios that combines the risk-free assets and the portfolio $a$:

$$E(r_p) = r_f + \frac{\sigma_p}{\sigma_a}\Big(E(r_a) - r_f\Big)$$

**Definition 3.1.2** *Given a portfolio with risky assets, a and a risk-free asset, the Sharpe ratio consists of the slope of the CAL and is given by* $\dfrac{E[r_a] - r_f}{\sigma_a}$.

The Sharpe ratio measures the risk premium per unit of risk, therefore the higher the Sharpe ratio, the better the investment.

When we combine the risk-free asset with a portfolio of risky assets, the efficient portfolios belong to the CAL with the biggest Sharpe ratio. To narrow it down, the portfolio with the largest risk premium per unit of risk is the solution of the following problem,

$$\max_{(w_1,w_2,\dots,w_n)} \quad \frac{E(r_a)-r_f}{\sigma_a}$$
$$\text{s.t.} \quad \sum_{i=1}^{n} w_i = 1$$

which will be the CAL tangent with the hyperbole. Going into specifics, the portfolio located in the tangency is called by market's portfolio $M$, which weights can be calculated directly by

$$w_M = \frac{\Sigma^{-1}(\mu - r_f\mathbf{1})}{A - Cr_f}.$$

Thus, we conclude that the efficient portfolios combine the risk-free asset with the market portfolio. This tangent CAL is called the Capital Market Line (CML). Therefore, the CML is the CAL where the portfolio of risky assets consists of the market portfolio

$$E(r_p) = r_f + \frac{\sigma_p}{\sigma_M}(E(r_M) - r_f).$$

When there is a risk-free asset, the efficient portfolios are located in this line in the $(\sigma_p, E(r_p))$-space. The Figure 2.2 displays the representation of the CML and market portfolio.

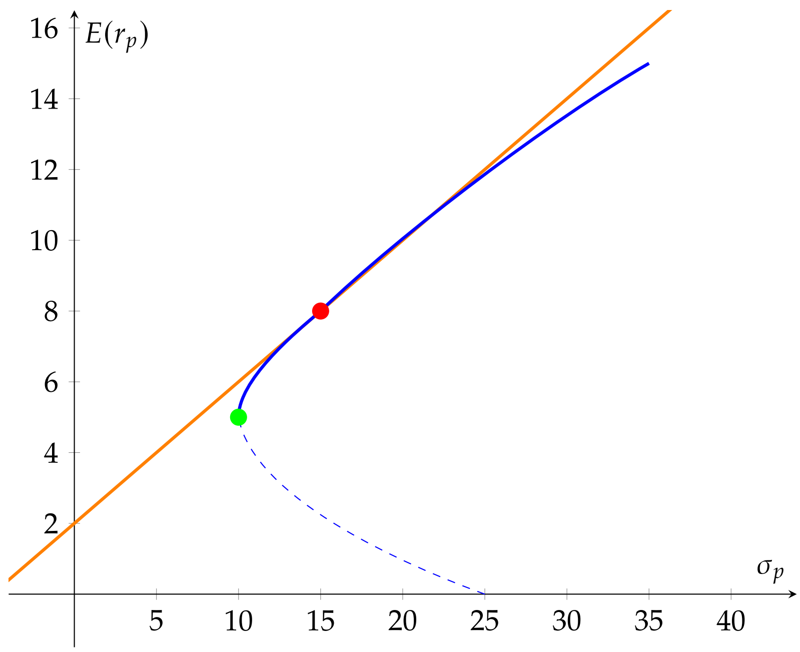


Figure 3.2: Capital market line example illustrated by the orange line, containing the market portfolio in the red dot.

### 3.1.5 Pricing in the CAPM

The pioneering ideas of Markowitz (1952) inspired other theoretical researchers who played a part in the birth of portfolio theory, such as Tobin (1958), Treynor (1961), Sharpe (1963,1964), Lintner (1965), and Mossin (1966).

**Definition 3.1.3** *Given a portfolio p and the market portfolio M, the* ***beta*** *of the portfolio p is the covariance between the portfolio and the market portfolio divided by the variance of the market portfolio,* $\beta_p = \dfrac{\sigma_{pM}}{\sigma_M^2}$.

When investors have mean-variance preferences, we can deduce a pricing equation, that relates the expected return of each portfolio with the market risk premium, $E(r_M) - r_f$, and its covariance with the market portfolio, $\sigma_{pM}$. The following equation represents the Security Market Line (SML).

$$E(r_p) = r_f + \beta_p(E(r_M) - r_f)$$

where $\beta_p = \dfrac{\sigma_{pM}}{\sigma_M^2}$.

Stated differently, by being the slope of the SML, the market risk premium reveals the additional returns above the risk-free rate as compensation for investing in risky assets.

In consideration of the definition stated earlier, the beta of a portfolio is a measure of the relation between the risk of the portfolio and the risk of the market. Berk and DeMarzo (2007) described it as "is the expected % change in its return given a 1% change in the return of the market portfolio". The advantage of the value of $\beta_p$ will depend on the type of investor, investment or company in mind.

- If $\beta_p > 1$, the portfolio is strongly affected by the influence and fluctuation of the market in the sense that it is more volatile than the market portfolio and it outperforms the market. In this case, it is good in times of boom because portfolio returns are expected to be higher than market portfolio returns, and bad in times of hardship (lower return). This is the case of cyclical industries, where profits and revenue have big oscillations throughout the business. This value of beta is also common in small and tech companies and growth stocks. New and innovative businesses build great expectation within their market and value, which leads to capital appreciation. There are some investors and day traders who value this, when looking for a more direct investment from the changes of share prices with expectations of market rising, although it is unforeseeable;

- If $\beta_p = 1$, the portfolio returns will behave similarly to market portfolio returns, so there are no hopes of the portfolio outperforming the market;

- If $\beta_p < 1$, the portfolio is less turbulent than the market portfolio, which is the case for most companies. This is positive in times of depression and negative in stages of sudden rising in the market. Non-cyclical firms tend to have a beta like this. Risk-averse investors find this beta preferable, since they have more realistic expectations (with less risk).

Hence, $\beta_p$ acts as an indicator for the risk of the portfolio and its performance since it measures systematic risk, that it, the risk that can not be eliminated through diversification. Whether it's good or bad has to do with investor preferences. Very risk-averse investors prefer portfolios with low betas and less risk-averse investors prefer portfolios with high betas.

When evaluating a portfolio performance, solely considering it's returns leaves an incomplete and limited view of the actual accomplishment. For that, there's another indicator, $\alpha$, to verify whether the risk taken was worth for said return. Before defining the next important portfolio performance indicator, $\overline{\mu}_p$ is the empirical average of the portfolio's daily returns.

**Definition 3.1.4** *Given a portfolio p and the market portfolio M, the* ***alpha*** *of the portfolio p is the distance between the expected return ($\overline{\mu}_p$) and the expected value of the portfolio's return defined by the SML, that is,*

$$\alpha_p = \overline{\mu}_p - r_f - \beta_p\big(E(r_M) - r_f\big).$$

This constant, $\alpha_p$, indicates the stock's historical performance compared to the expected return estimated by the SML, by being the distance above or below the SML. It represents the deviation of the historical stock's average return from the SML, which can be positive or negative. Therefore, $\alpha_p$ can be interpreted as a risk-adjusted measure of the stock's past performance.

- If $\alpha_p > 0$, the portfolio obtained more returns than expected by the SML measured by the $\beta_p$. This is the best case scenario to look out for;
- If $\alpha_p = 0$, the SML deducted exactly how the portfolio was going to perform, so there is no excess return, although it's a rare event;
- If $\alpha_p < 0$, the returns did not comply the returns expected by the SML, thus the portfolio performed poorly.

## 3.2 Alternative Methods for Quantifying Risk

### 3.2.1 An Overview of Value at Risk

Although we've gone over the concept of variance as a measure of risk, there was still a need for a simple tool to scrutinise the worst scenarios of an investment.

**Definition 3.2.1** *Given a level of significance $\alpha$ and a portfolio $p$,* ***value at risk****, $VaR(\alpha)$, is the maximum potential loss of portfolio returns over a given time horizon and with a confidence level $1-\alpha$, that is, $VaR(\alpha)$ satisfies $P\big(r_p < -VaR(\alpha)\big) = \alpha$.*

The origins of value at risk can be difficult to trace, due to the lack of academic literature and being mostly associated with internal projects in businesses. Adamko et al. (2015) state that the first ever attempt to measure potential losses within an investment in a portfolio goes back to 1888 with the statistical theory studies of Francis Edgeworth. In his contributions, he spoke in favour of the usage of past evidences for predictions in the future.

Later, Leavens (1945) thought of a quantitative example of ten government bonds in a paper to emphasize the benefits of diversification. In his exercise, Leavens (1945) assumed that bonds were independent, so either the bond would be worth \$1000 at maturity, or be worthless if the agreed conditions are not satisfied. The portfolio's value presented a binomial distribution at the end of the horizon. In result, his portfolio had a $VaR$ of \$948.69. Although he never specified the name of the measure in his non-technical discussion, he referred it as "the spread between the likely profit and loss". This is considered the first ever mention of value at risk to this day.

After the World War II, most currencies went through a period of devaluation and corporations kept their ongoing hedges because planned devaluations were only known by the governments, which produced a lot of risk in foreign exchanges. Lietaer (1971) focused on solving this issue with a method for hedges' optimization through a practical VaR measure. With help of the diagonal model by Sharpe (1963), Lietaer (1971) obtained the VaR measure with the variance of market value VaR metric and assumed randomness in devaluation moments, with the conditional influence of a devaluation being normally distributed. This study can be considered the first application of the Monte Carlo approach in a VaR measure.

Despite of the previous work and thought put into the concept of potential losses, the birth of the current value at risk is credited to the JP Morgan investment bank. Back in 1994, its chairman Dennis Weatherstone created a task for a simple tool that would cover the complete range of risks encountered by the bank in the coming 24 hours, called 4:15 report. JP Morgan's RiskMetrics Group satisfied that longing for measuring and aggregating various types of risk of different trading activities in a single methodology with the creation of the Value at Risk. This loss indicator was estimated with Markowitz's Portfolio Theory at its core. Since then, VaR was quickly accepted and implemented in other systems and standardized measures of financial risk. Its versatility and range of risk categories grasped a variety of financial institutions' attention, such as banks, pension funds, securities houses, and more (see Longerstaey and Spencer (1996), Souza (2017)).

> "Value at risk traces its roots to the infamous financial disasters of the early 1990s that engulfed Orange County, Barings, Metallgesellschaft, Daiwa, and so many others. The common lesson of these disasters is that billions of dollars can be lost because of poor supervision and management of financial risks. Spurred into action, financial institutions and regulators turned to [VaR], an easy-to-understand method for quantifying market risk" (Jorion, 2007).

The VaR became a key measure that regulators use to fulfill the capital requirements of financial institutions.

### 3.2.2 Value at Risk in a Normally Distributed Portfolio

When we have a normally distributed portfolio, we can translate the portfolio variance into a VaR measure. Let's suppose that all individual asset returns follow a Normal distribution. The linear combination of the normal random variables is also normally distributed, making up the normal distributed portfolio. By translating the confidence level $c$ into a standard normal deviate $\alpha$ for the probability of losing more than $-\alpha$ is $c$, we can calculate the VaR of a normally distributed portfolio with $W$ as the initial portfolio value,

$$VaR = -\left(\mu_p + \Phi^{(-1)}(\alpha)\sigma_p\right)W = -\left(\mu_p + \Phi^{(-1)}(\alpha)\sqrt{w'\Sigma w}\right)W,$$

with $R_p \sim N(\mu_p, \sigma_p^2)$.

Due to the nature of VaR and its calculation, a lower value of variance (risk) will therefore lead to a lower VaR.

### 3.2.3 Historical Value at Risk

When we do not know the theoretical distribution of the portfolio returns but have a large representative sample, we can compute the historical VaR, i.e., in an empirical method.

A large sample of past portfolio returns makes it possible to simulate the probability distribution function and obtain the estimator of VaR. On account of this, there is no need to hypothesize how the risk factors are distributed (Souza, 2017). Even without requiring knowledge of the data's distribution, there's the assumption that the past trends tend to repeat themselves (Khindanova & Rachev, 2019).

Let $n$ be the length of the sample and $\alpha$ as the level of significance. Since we're dealing with a historical data set, we can calculate the historical VaR by sorting the sample in ascending order and obtaining the element in the position interger of $n\alpha$. In other words, the historical VaR is the quantile of order alpha of the empirical distribution of returns.

### 3.2.4 Monte Carlo Approach

During his work in the analysis and contributions to nuclear bombs, Ulam (1991) found that numerical simulations would support in mathematical problems with integrals within the theory of nuclear chain reactions. With the help of his friend John von Neumann in 1946, this idea came into life with the name of Monte Carlo, since it works as a game of luck in a computer making various random guesses with statistical techniques to deduct the right assumption. The premise of the Monte Carlo is about repeated simulation of a random process for interest and price of assets as variables with past observations in mind, which embraces a diverse array of potential scenarios. The probability distributions and parameters of the variables are known from the beginning so these simulations generate an entire distribution of portfolio returns, where VaR can be derived from (Jorion, 2007). The Monte Carlo method can be divided into two parts: stochastic process and parameters for the financial variables; simulations of hypothetical movements of price of assets.

In any Monte Carlo process, it starts with the identification of assets and risk factors. The second step is deciding on the best explanatory model for the behaviour of risk factors. Afterwards, there is the estimation of parameters via historical past data for the modelization and subsequent stochastic simulation of hypothetical situations of risk factors. Resulting from this, there is an approximate estimation of portfolio value, with the distribution of possible returns and transformation of returns into losses and gains for the portfolio. In the end stands the creation of an histogram of returns, with the percentile corresponding to the desired VaR.

Jorion (2007) argues that the Monte Carlo approach is the most powerful tool for the computation of VaR as it is able to capture a wide variety of risk and scenarios.

### 3.2.5 Historical Tail Value at Risk

VaR does not take into account the likelihood and impact of extreme events with severe losses ("tail risks") that fall outside the normal range of market conditions. This leads us to consider another measure that satisfies this property.

**Definition 3.2.2** *Given a significance level $\alpha$, the* ***expected tail loss (TVaR)*** *is the expected loss beyond the $VaR(\alpha)$ level,*

$$TVaR_\alpha(R_p) = -E[R_p|R_p < -VaR(R_p)] = \frac{1}{\alpha}\int_0^\alpha VaR_v(R_p)\,dv$$

The TVaR can provide a more accurate assessment of potential losses in the worst-case scenario. By focusing on the tail-end of the distribution of potential losses, TVaR provides a more realistic and safe estimate of the risk than the VaR.

Given the empirical sample of returns sorted in ascending order $(r_1, ..., r_n)$, we are going to use the following estimator of TVaR, $_\alpha$:

$$TVaR_\alpha = -\frac{1}{n\alpha}\left(\sum_{k=1}^{[n\alpha]-1} r_{(k)} + (n\alpha - [n\alpha] + 1)r_{[n\alpha]}\right)$$

with $[n\alpha]$ as the largest integer value lower than $n\alpha$ or the integer part of $n\alpha$.

Chapter 4

# Factor-based Investment Strategies

## 4.1 Chronological Introduction

**Dogs of the Dow** strategy (DoD) was developed by O'Higgins and Downes (2010) in their book "Beating the Dow", first published in 1991. The creators of this investment strategy were contrarians and successfully developed a simple technique for investors who'd like to capitalize on volatility in short-term horizons. Furthermore, a minimalist method with a shorter universe than usual offers flexibility and straightforwardness by being yearly investments. One of the main features of this technique is the selection of corporations in the North American universe since the only organizations considered belong to the Dow Jones Industrial Average (DJIA). Within the thirty Dow assets selected by market capital, the idea is to buy the ten top stocks yearly depending on their dividend yield. The technique of investing in the ten highest-yielding stocks yearly with a 12-month holding period from 1973 through 31 December 1998 led to a 7264% cumulative total returns, excluding taxes and commissions. This experience proved to be consistent in surpassing moments of alarming volatility and outperforming any kind of market (O'Higgins & Downes, 2010).

Just two years later, in 1993, Jegadeesh and Titman (1993) proposed an approach relying on historical performance as a reliable forecaster called "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency". More specifically, they prioritized businesses with high returns (winners) by buying their liabilities and disregarded companies with low returns (losers) by selling their assets. We'll refer to this strategy as **Buying Winners and Selling Losers** (WL). This kind of method based on the companies' momentum (trading strategy) was applied in different durations of investment and holding periods. The data used was part of the CRSP daily returns (NYSE and AMEX stocks) from 1965 to 1989. In the end, Jegadeesh and Titman found significant abnormal returns during this period. More specifically, the strategy examined in most detail, which selected stocks based on their past 6-month returns and held them for 6 months achieved an average compounded excess return of 12.01% per year. On another hand, whilst examining the returns of stocks 36 months after the formation period, stocks in the winners' portfolio brought higher returns. "However, the announcement date returns in the 8 to 20 months following the formation date are significantly higher for the stocks in the losers portfolio" (Jegadeesh & Titman, 1993).

A new method of evaluating a company's historical data was then introduced by Piotroski (2000) in the paper "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers". According to his viewpoint, there is an unique opportunity in investigating and investing on undervalued firms, based on their book-to-market (BM) ratio. Piotroski then designed a simple fundamental analysis composed of nine factors for identifying the firms he believed were the most likely to succeed and prosper, built on profitability, debt, and operating efficiency. Thanks to its score-like nature, we'll call it **F_score**. The chosen period of data was from 1976 to 1996, and some results showed that choosing winner shares (with a score of 8 or 9) within high BM firms increased at least 7.5% annually than without the initial BM screening. Additionally, a strategy not only focused in buying winner stocks but also in selling loser ones (score of 0 or 1) revealed an average annual return of 23%. Another conclusion was that the "healthiest" corporations, within the high BM ones, appeared to generate the strongest returns, which contradicts the idea of Fama and French (1992) that "the BM effect is related to financial distress" (Piotroski, 2000).

Further on, in 2006, Greenblatt published the book "The Little Book That Beats The Market" the **Magic Formula** (MF), which seeks to identify companies undervalued by the market, based on their capital efficiency and earnings. Greenblatt created a simple formula with the idea of having an investment more profitable than placing the same amount of money in a risk-free U.S. government bond for ten years. This approach is also considered a type of value investing considering the search for shares at a bargain price. The universe in this case consists of the 3500 largest companies (based on high market capitalization) available for trading on one of the major U.S. stock exchanges, excluding financial and utility stocks (for reducing specific risk) and assets with limited liquidity. A yearly investment from 1988 to 2004 in thirty stocks with the highest combination of high earnings yield and high return on capital resulted in returns of 30.8% per year, whilst the market average return is about 12.3%. The magic formula outperformed the market in 14 of those 17 years. To steer clear of short-term market fluctuations, the ideal horizon is long-term, e.g., a minimum of three to five years (Greenblatt, 2006).

## 4.2 Factor Bases

- **Revenue** total amount of money obtained through sales of services and goods of a business;

- **Interest** cost of borrowing money;
- **Tax** compulsory financial charge collected by the government from businesses, individuals and other entities to cover the cost of general goods, services and activities;
- **Net income** quantity of capital a company has gained after subtracting interests, taxes and expenses from total revenue; comes in the statement of financial performance or income;
- **Debt** amount of capital that is owed or past due;
  - **Short-term debt (STD)** debt with a maturity of 12 months or less;
  - **Long-term debt (LTD)** debt that is due in more than a year;
- **Asset** resource or property of a company that can be owned and has value;
- **Liability** obligations a company owes to others;
- **Cash and cash equivalents (CCE)** value of a firm's assets that are easily converted to cash;
- **Equity** residual value of shares issued by a company;
- **Depreciation** reduction in the value of an asset over time;
- **Amortization** gradually decreases the debt through the repayments agreed with the lender;
- **Working Capital** subtraction between current assets and current liabilities;
- **Shares Outstanding** total number of shares issued and actively held by stockholders.

## 4.3 Types of Factors

There are two main types of factors: fundamental and technical. Firstly, fundamental analysis has the intrinsic value of an investment as its purpose, with quantitative and qualitative factors in mind. Earnings, expenses, revenue growth, profitability, cash flow, and debt levels are examples of fundamental factors, from which we can infer the performance of a firm. These fundamental factors take place in value and contrarian investing. On the other hand, technical analysis focuses on historical price and volume data of an investment to identify patterns and trends, as an attempt to predict future price movements and to search for lucrative and advantageous opportunities. Some technical factors can be moving averages, volume analysis, resistant levels, etc. The technical factors belong in momentum investing (Bender et al., 2013).

## 4.4 Dogs of the Dow

### 4.4.1 Factors

This strategy relies solely on two fundamental factors, the market capitalization and the dividend yield.

The market value of equity, or market capitalization (market cap) is given by the following equation

$$\text{market capital} = \text{shares outstanding} \times \text{ market price per share}.$$

Berk and DeMarzo (2007) stated that the market value relies on the expectations of the firm's assets in the future, rather on the historical cost of the asset.

Put simply, dividends are payments made by companies to their shareholders, i.e. they represent the distribution of the company's recent profit to its owners and reward for having invested in the company. In this way, the dividends have become a source of information for investors as a demonstration of business performance (Woolridge, 1983). The dividend yield is a financial metric that measures the annual dividends paid out by a company relative to its stock price; it is expressed as a percentage, calculated by

$$\text{dividend yield} = \frac{\text{annual dividend per share}}{\text{current stock price per share}}.$$

### 4.4.2 Methodology

Briefly, this strategy consists in investing yearly in the ten highest dividend-yielding stocks that belong to the Dow Jones Industrial Average (DJIA). For this, we need to understand its universe and steps.

At first, the universe is composed of the thirty companies within the DJIA, i.e. the thirty biggest companies in the American Market. To be included in the DJIA, the company must be listed on the New York Stock Exchange (NYSE) or the NASDAQ and possess a strong and stable financial reputation and substantial market capitalization. The DJIA is obtained by selecting these thirty best companies on the S&P500, based solely on market capital, which works as a fundamental factor for specifying the universe.

The other fundamental factor relevant to this strategy is the dividend yield. Then we sort them by the factor considered, from highest to lowest in this case. The top ten companies from the rank are then considered the best ones, which will be designated as "Dogs of the Dow".

In this way, the portfolio is created with these ten companies and we invest equally in them, by holding the stocks for one year and selling them out by the end of the year. Only then, we repeat the cycle and update the ranking of the thirty original companies by selling the stocks that failed to stay in the top ten (average about three or four per year) and buying the ones that measured up and go over the same process every year.

### 4.4.3 Motivation

In this section, we describe the importance and motivation of the fundamental factors brought by the authors.

O'Higgins and Downes (2010) believe that the Dow is a popular index representative of the most powerfull equities in the U.S., and even the world.

> "Combined, the 30 Dow components have assets of around 2.5 trillion dollars, nearly five million employees, and sales that exceed the gross national products of every country in the world except China, Germany, India, Japan, and the United States" (O'Higgins & Downes, 2010).

These businesses can go through drastic times of rising, falling, merging, reorganizing, leaving and rejoining the Dow and even suceeding post-bankrupcy. In a sense, they exhibit a remarkable adaptability and resilience, firmly establishing their presence. Due to some of these evolutions, a majority, if not all, of the key sectors in the American economy belong in the DJIA. O'Higgins and Downes (2010) mention cyclical stocks in their book, which will pass through times of overreaction and then reacquire their value reflecting their actual risk. They're confident that even if Dow stocks are cheap, surprises of major adverse financial developments are minimal, "because the Dow stocks are so highly visible and widely [analysed]", and the Dow stocks can even help turn around situations like bankruptcy.

The main determining factor in stock prices is earnings. According to O'Higgins and Downes (2010), choosing stocks with a high dividend yield is extremely effective, especially because even if stock prices rely on earnings expectations, they are truly sustained by dividend payments in cash flow. Initially developed in 1991, this strategy likely didn't necessitate a complex array of factors to identify neglected company assets, thus retaining its contrarian nature. Consequently, a high dividend yield can result as an indicator for a contrarian strategy because it shows an asset with a low price in relation to the dividend when there are doubts about the firm's next earnings prospects, as outlined by O'Higgins and Downes (2010). Moreover, O'Higgins and Downes (2010) state that companies that don't distribute dividends tend to fall into one of these two categories: cash-strapped organisations with limited resources (low earnings), and growth companies that reinvest their earnings to fuel rapid expansion, which both are not interesting for a well-thought investment. On top of that, the risk of suspension or lowering of dividends in a company within the U.S. is smaller than the risk of fluctuation of returns and stock price. This arises from the rarity for a North American company to decrease or suspend dividends, being a last resort situation.

## 4.5 Buying Winners and Selling Losers

### 4.5.1 Factor

This strategy is based on momentum. Buying winners and selling losers is a trading strategy that involves buying stocks that have been trending up in price and selling stocks that have been trending down in price, which is a way of technical analysis. This method is based on the idea that stocks with recent good performances will perform better in the future than stocks that have been performing poorly, which will continue to do so. In other words, it follows the idea that past performance is an indicator of future achievements.

The WL strategy is based on its own name. That is to say, this process involves buying stocks that have been excelling recently and selling stocks that have been lagging behind. Jegadeesh and Titman (1993) opted to classify value stocks using the technical factor of relative strength (RS), which represents a method within momentum investing. To put simply, RS measures a stock's price change over the last period of time chosen relative to the price change of a market index. As a technical indicator, it exclusively relies on historical price.

### 4.5.2 Methodology

First and foremost, there's the decision of the ranking period, that is, amount of time over which the investor does the ranking of the companies, after the last ranking and normally it is about six months.

Then, at the beginning of each month, the stocks are ranked based on their RS over the ranking period (six months). The bottom decile consists of the losers and the top decile comprises the winners.

The next step consists of building the portfolio monthly, by investing equally in the winner stocks and short selling also equally the loser stocks. Short selling is defined as borrowing a security whose price we foresee it's downfall and selling it open on the market. The positions are held for six months.

Lastly, the portfolio undergoes a rebalancing process. This involves adjusting the winners portfolio on a monthly basis by selling the winners that have dropped in the rank based on their latest returns and buying new winners that have risen in rank. The rebalancing is only finished when the number of assets of the portfolio corresponds to decile of the stocks in the original universe. This procedure continues for as many years as the user wants, since it's supposed to generate short-term profits.

## 4.6 F_score

### 4.6.1 Factors

This strategy is based on the formation of the universe through the book-to-market ratio, and nine other fundamental factors that together produce a defining score to decide whether an asset is worth investing, within the universe. This system of awarded points delineates a scale from zero to nine to comprehend the genuine value of undervalued stocks, e.g., to separate winners from losers, in line with the paper's title.

**Inital Factor.** As previously mentioned, this method begins with an universe dependent on the book-to-market ratio.

"The book value of an asset, as indicated in a firm's financial statements, is equal to its acquisition cost minus accumulated depreciation" (Berk & DeMarzo, 2007) and the market value of equity is defined as the company's market capitalization , since it's equal to value of outstanding shares evaluated by the marker price per share. Therefore, it's simple to understand that the book-to-market ratio (BM) is calculated by

$$\text{book-to-market ratio} = \frac{\text{book value of equity}}{\text{market value of equity}}.$$

This ratio serves as a way to infer whether the market is valuing the company's equity cheaply (or not) compared to its book value. It's extremely rare to have a $BM > 1$, which essentially means that the share price is lower then the company's worth if it were liquidated in the moment (fire sale). So generally, the ratio exceeding the value of one can indicate that the stock price of a company is trading for less than the worth of its assets (undervalued). On the contrary, a ratio below one could indicate that a company has positive projections on future profit and investors are willing to pay more for a company than it's net assets are worth as a premium for that possibility of growth (overvalued). Even though it is extremely rare to obtain a BM higher than one, when it happens it really is a once-in-a-lifetime opportunity and value investors raise the assets' price, making the BM lower than 1 quickly. Even so, value investors like to use this ratio to grasp an idea of the state of value of equities (Graham, 1965).

**Factors within the F_score.** Piotroski (2000) then developed a ranking based on points from nine distinct signals, as an evaluation of a company's profitability and investment potential. This type of ranking, called F_score, will determine the high firms and select a portfolio with only their stocks.

The nine signals on which the F_score is based on are the following:

- Return on Assets (ROA) is calculated by

$$\frac{\text{net income + interest expense}}{\text{book value of assets}}$$

  and it's classified as a ratio for measuring how profitable a company is according to its total assets as it is sensitive to working capital. In this sense, a higher ROA indicates more efficiency and proficiency at managing its balance sheet for generation of profits. Although this seems like a pretty reasonable signal to stand on its own, companies from different industries have different asset bases.

- Cash Flow from Operations (CFO) is obtained by

$$\frac{\text{net income + depreciation and amortization}}{\Delta \text{ working capital}}$$

and it is the first section represented in a company's cash flow statement, indicating how much money it brings from various activities such as the service it provides to its costumers, selling and/our manufacturing products, etc, and where it comes from. This last part is very convenient for business owners in understanding how to make their business bigger and more profitable, by maintaining enough cash for operational efficiency, paying out dividends to reward their shareholders and buying back shares for a stronger financial stance, for example.

- Leverage is given by

$$\frac{\text{total debt}}{\text{total equity}}.$$

As we can easily observe on its formula, reveals a company's debt in relation to the capital its shareholders invested in it (equity). By this end, this ratio shows the capability of a company to repay all of its debts with its funds.

- Liquidity as the ratio

$$\frac{\text{current assets}}{\text{current liabilities}}$$

indicates a company's ability to acquire cash from its loans or assets.

- Gross Margin Ratio (GMR) given by

$$\frac{\text{gross profit}}{\text{total revenues (sales)}}$$

is a profitability ratio for the percentage of each monetary unit of revenue that comes from gross profit.

- Asset Turnover (TURN) as the ratio

$$\frac{\text{total sales}}{\text{opening total assets}}$$

is meant to show the efficacy of a firm on generating revenue through its assets.

### 4.6.2 Rank and Methodology

Piotroski (2000) firstly decided to select the top quintile corporations, depending on their book-to-market ratio, to develop the universe for the yearly investments.

Then, the ranking of Piotroski's strategy is structured as a score, the F_score, which is calculated as the sum of nine different signals. The creator of this methodology divided it in three important bases for analysing the wellness of a company: Profitability; Leverage, Liquidity and Source of Funds; and, finally, Operating Efficiency. These signals have equal weights, in a way that no signal is more important than the other. This is accomplished by a binary-type rating on each signal studied.

Signals on Profitability

Evaluating a firm's profitability comes from checking its ability to generate funds and positive cash flows through operating activities. A positive slope suggest improvement on its future. To this end, we have the signals ROA and CFO. For the calculation of the F_score, we have the following simple rules, where the delta symbol (Δ) signifies the variation in value between two consecutive years.

- F_ROA = 1 if ROA > 0;
- F_CFO = 1 if CFO > 0;
- F_Δ_ROA = 1 if Δ_ROA > 0;
- F_ACCRUAL = 1 if CFO> ROA.

Signals on Leverage, Liquidity and Source of Funds

Now, the next three financial signs give us an idea of the firm's situation regarding its capability to meet future service obligations by measures of capital structure. With that said, we check the leverage and liquidity in this part.

- F_Δ_LEVERAGE = 1 if ΔLEVERAGE < 0;
- F_Δ_LIQUID = 1 if Δ_LIQUID > 0;
- F_EQ_OFFER = 1 if the firm did not issue common equity in the year preceding portfolio formation.

Signals of Operating Efficiency

These last two signals are designed to give us a sense of the efficiency of the company's operations and activities and for that, we have the gross margin ratio and the asset turnover.

- F_Δ_MARGIN = 1 if Δ_MARGIN > 0;
- F_Δ_TURN = 1 if Δ_TURN > 0;

Finally, we sum every F_FACTOR to obtain the F_SCORE. According to the creator of this ranking himself, we must consider firms with a score of 8 and 9 ”high firms” and others with scores of 0 or 1 ”low firms”. Finally, the method ends with buying and holding the winners (high firms) and selling the losers (low firms) yearly. For an investment longer than a year, the rebalancing process is also done yearly and so the universe and chosen stocks can change every year.

### 4.6.3 Motivation

Piotroski (2000) found high BM firms specially intriguing for taking advantage in investments. High BM businesses tend to have less forecasts and coverage for possible stock recommendations so they are more neglected. This underrepresentation can be useful for a value investing opportunity because of potential for price appreciation, and even times of market inefficiencies, where investors can benefit from the subsequent market correction. They also have limited access to most informal information dissemination channels and are less credited given their recent poor performance. Besides this, they often face financial distress and their valuation primarily focuses on characteristics readily derived from historical financial statements, which serve as the most accessible and reliable source of information for these companies. These facts make the process solely fundamental and therefore much simpler.

## 4.7 Magic Formula

As mentioned previously, this strategy is based on the principle of value investing, which involves buying stocks from profitable and reliable businesses that are undervalued by the market and selling them when they reach their fair value. To find shares at bargain prices, Greenblatt (2006) states that a higher earnings yield highlights companies that earn more relative to their price. To differentiate good businesses from bad ones, a higher return on capital emphasizes organizations that invest their own capital to generate high profits.

### 4.7.1 Factors

The Magic Formula involves two key factors or metrics: earnings yield and return on capital.

Earnings yield is the following ratio

$$\text{earnings yield} = \frac{\text{EBIT}}{\text{enterprise value}}.$$

For this, earnings before interest and taxes (EBIT) is calculated by information from the income statement

$$\text{EBIT} = \text{net income} + \text{interests} + \text{taxes}.$$

This signal is preferable to reported earnings for comparisons of different enterprises, since they operate with different tax rates and levels of debt.

For the denominator, the enterprise value not only takes into consideration the price paid for an equity stake at the business, but also bears the debt assist in generating operating earnings. Enterprise value can be calculated by the following equation,

$$\text{enterprise value} = \text{market value of equity} + \text{net debt},$$

with $\text{net debt} = \text{STD} + \text{LTD} - \text{CCE}$. Greenblatt calculates EBIT by

$$\text{EBIT} = \text{EBITDA} - \text{maintenance cap/expenditure}.$$

EBITDA stands for earnings before interest, taxes, depreciation and amortization.

Return on capital is the following ratio

$$\text{return on capital} = \frac{\text{EBIT}}{\text{net working capital} + \text{net fixed assets}}$$

The denominator of the ratio substitutes total assets to determine how much capital a business needs. For that, we have the net working capital as the capital spent on inventory and receivables, and net fixed assets as capital invested by a company for purchasing fixed assets essential for its business activities. The Return on capital is supposed to measure how efficiently a company is using its capital to generate profits.

### 4.7.2 Methodology

Within an universe of businesses listed on one of the prominent U.S. stock exchanges for trading, Greenblatt (2006) considers the 3500 largest of those businesses, depending on their market capitalization, whereas the higher, the better. Greenblatt (2006) also eliminates all utilities and financial stocks such as banks, mutual funds, insurance companies, because of their financing by large amounts of debt (high leverage).

Following that, the method implies a yearly selection of thirty stocks to invest in that year, for a minimum of three years to benefit from interesting long-term results. For the selection of stocks, we rank stocks by earnings yield, with the highest assigned a score of 1, second highest with a score of 2 and so on. The same stocks are also similarly scored by return on capital, with the highest also assigned a score of 1. Afterwards, we add the two scores of the stocks, such that both fundamental factors have an equal influence in which stock to choose at the same time. Hence, in the absolute best-case scenario, the "perfect" stock, is the one with a score of 2.

Although we've just gone over with the process, there are still two different ways to apply this method.

1. The simpler approach:
   a) Create an equal-weighted portfolio with the thirty lowest scoring assets all at once yearly;
   b) After the year passes, collect the returns and repeat the process, with a new ranking and selection.
2. The more complex approach:
   a) In the first year, choose from five to seven stocks for an equal-weighted portfolio, investing only 20% to 33% of the capital intended to invest;

b) Repeat point (a) every two or three months until there is no more capital to spend. This step would usually take from nine to ten months to complete and possess a portfolio with twenty to thirty stocks;

c) Each asset should be sold after one year of holding it.

- Winner stocks should be sold after a few days after a year;
- Loser stocks should be sold a few days before the ending of the year deadline.

d) Repeat the process, by replacing the sold assets and taking advantage of the earnings.

In this work, we've used the simple approach of the MF.

### 4.7.3 Motivation

As mentioned previously, the MF is summarised in a method to buy shares of businesses that invest their own capital at high rates of return, at bargain prices. In other words, businesses that achieve a high return on capital, "invest some or all of its profits at a very high rate of return [which] can contribute to a very high rate of earnings growth" (Greenblatt, 2006). This is a special advantage, because most individuals and companies can invest their capital only at average rates of return. It also prevents competitors from eradicating a high return on capital company's above-average profits. Businesses that aren't up-to-date nor popular earn average or below-average return on capital, in general, which easily attracts competition.

Additionally, buying a high earnings yield means that the individual will buy companies that earn much more, compared to the price paid for. As Greenblatt (2006) puts it, "the formula is systematically helping us find above-average companies that we can buy at below-average prices".

# Chapter 5

# Exploring Qrumble

In a nutshell, Qrumble is a Python framework for streamlined factor investing being developed in the Computer Science PhD of Santos (2023). It provides a Python library and a toolbox used from the command-line. Through its nature and resources, it is designed to process data, predict future performances based on historical past data and analyse investment strategies depending on various fundamental and technical factors. The version of Qrumble implemented in this work was the v2.96. The Qrumble manual is currently going through some updates, but is recommended for more thorough information (Santos, 2023).

To put simply, Qrumble makes it simple and direct for a user to design a factor model through one or multiple ranking and/or screening criteria, choose stocks based on the factor model implemented, assigns weights to the selected stocks based on a weight function (equal-weighted by default, but other weighting functions can be used, e.g. value-weighed), set a time horizon, fees, period of rebalancing and, finally, run the investment strategy with a real financial data set for multiple time periods. In the end, one can check for the portfolio evaluation metrics, such as return on investment (ROI), annualized ROI, mean of returns, standard deviation of returns and Sharpe value. One contribution within this work was the implementation of more metrics, such as beta, alpha, VaR and TVaR, and two other weighting schemes, the minimum variance portfolio and the market portfolio.

Currently, Qrumble is focused on long-term investment experiments, but supports two trading strategies which are **buy and hold** as a default – buying at the beginning of the investment and selling them at the end – and **short selling** – initially selling stocks with the intention of purchasing them later on. In order to replicate more accurately the dynamics of the stock market, transaction fees as a percentage of the investment can be implemented on each trading operation. Other costs like interest rates, taxes and foreign exchange fees are yet to be implemented on this tool. Nonetheless, we chose to not implement fees within our experiments.

## 5.1 Data

Although the user can provide the financial sample desired to run and experiment, Qrumble already possesses two financial samples of STOXX600, the 600 largest companies in Europe by market capitalization, in two different time periods.

More specifically, the data frame is consisted of two pandas samples jointed together, the OHCLV data frame, which possesses daily market data including Open, High, Low, Close, Volume measures, and the FUNDAMENTALS data frame,which holds the asset's fundamental data reported on a semi-annual or yearly basis. The first data frame is obtained through Yahoo! Finance and the second is sourced from Robur dataset via Nasdaq Datalink (formerly Quandl) (Robur, 2023).

The universe, the list of all stocks that could be picked by an investment strategy, is composed of STOXX600 companies from 2014 to 2019, as a training sample, and 2018 to 2021, as a overfitting validation sample. In this work, we use the training sample, since we're testing the machine learning model. The STOXX600 index was taken from STOXX Ltd., which is owned by the Deutsche Börse Group. These time intervals are compelling and intriguing, by taking place in the aftermath of the financial crises and preceding the challenges posed by COVID-19 and inflation.

Another important key point is that the risk-free rate selected here was -0.6 per annum.

## 5.2 Qrumble's Metrics and Improvements

As mentioned previously, Qrumble provides five key indicators of the well-being of a portfolio.

- **Return on Investment (ROI)** the rentability in the end of the investment with no costs, for $T$ years.
  - If $T = 1$ and we have $n$ assets, ROI= $w_1 r_1 + w_2 r_2 + \dots w_n r_n$ in percentage, with $w_i$ as the weights and $r_i$ as the returns of each asset, $i = 1, \dots, n$. Each asset return is calculated by $\frac{\text{final price}-\text{initial price}}{\text{initial price}} \times 100$;
  - If $T > 1$, Qrumble reinvests the gains (losses) in each portfolio formation. ROI is the value of the portfolio $T$ years later, and it is independent between $t = 0$ and $t = T$. To compute the ROI after $T$ years, Qrumble calculates the compounded return. If we have $T$ yearly portfolios in $T$ years, each with $\text{ROI}_i$, $i = 1, \dots, T$, then ROI= $100 \times \left[\left(1 + \frac{\text{ROI}_1}{100}\right)\left(1 + \frac{\text{ROI}_2}{100}\right) \dots \left(1 + \frac{\text{ROI}_T}{100}\right)\right]$ in percentage;
- **Annualized Return** ROI scaled to an annual value. Annualized return is obtained by the compound annual growth rate, as in annualized return = $100 \times \left(1 + \frac{ROI}{100}\right)^{1/T}$ in percentage;

- **Mean** mean of daily returns times 252, in percentage;
- **Standard Deviation (St Dev)** standard deviation of daily returns times $\sqrt{252}$, in percentage;
- **Sharpe value**.

As stated earlier, Qrumble is also capable of running the same investment strategy in different weighting schemes. In pursuit of this, we have the equal-weighted portfolio (EWP) and the value-weighted portfolio (VWP). The EWP is easily constructed by investing the same amount of capital on every asset chosen. The VWP is another famous type of portfolio, where brokers invest money per stock in proportion to its market capitalization. These two types of portfolios remain the simplest and most used in real life.

Notwithstanding these metrics and types of portfolios, there were some suggestions implemented in Qrumble for a better understanding of the portfolio performance itself and two other portfolios with a different weighting scheme.

Firstly, the measures that contributed for a more thorough perception of the portfolio's outcome were the ones mentioned in **Chapter 3**. These metrics are computed in Qrumble with the daily stock returns.

- **Beta**;
- **Alpha**;
- **Value at Risk (VaR)**;
- **Tail Value at Risk (TVaR)**.

Following that, the two other portfolios introduced in Qrumble consist of the theoretical efficient portfolios explained in chapter 2. The minimum variance portfolio (MVP) gets its name by being the supposedly efficient portfolio with the lowest risk thinkable and the market portfolio (MKTP) is considered to be the theoretically efficient portfolio that combines assets with the risk-free asset. Both the MVP and MKTP represent two possible efficient portfolios in the scope of the CAPM, but their implementation onto real data is prone to error for a couple of reasons. At first, the impossibly broad application of capital in all assets as one of the assumptions of the CAPM. In this work, we are focused on selecting a number of interesting equities and then creating a portfolio solely based on them. In this way, the CAPM assumption of investment in every asset available is already being ignored. Another relevant constraint is the fact that the MVP and MKTP use the prior year of investment to construct the "perfect" weights for portfolio efficiency, but if the prices of every asset on the year of investment don't fluctuate in the same pattern/trend as in the previous year, then the results are compromised. These theoretical portfolios serve as a measure of possibility of more efficiency by analysis and computations for the supposedly best case scenario.

## 5.3 Methodology

In this section, we'll provide examples of various ways to utilize Qrumble, through coding scripts of some of the baseline strategies.

The first script below is essential for conducting any experiments using this Python framework. It establishes critical parameters such as the universe setup, the period selected, the risk-free rate, etc. For more detailed information on the various parameters and configurations, it is advisable to consult the Qrumble manual (Santos, 2023).

```python
from contextlib import contextmanager
import logging
import qrumble as q
from qrumble.factors import *
import qrumble.universe

FUNDAMENTALS="data-stoxx600/FUNDAMENTALS.2015_2019.pickle"
OHLCV="data-stoxx600/stoxx600.jan2014_dec2019.pickle"
RF=-0.6

q.configureLog(logging.BASIC)
q.weights.configureLog(logging.INFO)

#Load sample dataframes
funda = q.load(FUNDAMENTALS)
ohlcv = q.load(OHLCV)
```

Listing 5.1: Data implementation in Qrumble.

The testcase seen in the Listing 5.2 below consists of the code that defines the usual conditions and parameters for all investment strategies, such as the universe always chosen in `universe_list=q.universe.fetch`, the risk-free rate with `Rf=RF`, the null fees in `fee=0`, the level of significance for the computation of VaR and TVaR as `Alpha=0.05`, the portfolio weighting scheme in `weight_function`, and most importantly, the factors in the `criteria`. In this example, we're running a test with Dogs of the Dow on the MKTP, for five years since 2015 in `"jan2015", "5y"`, hence the yearly rebalance in `rebalance='1y'`. The one month periodicity in `periodicity='1m'` sets the table of results shown by Qrumble after running this code, which will show monthly returns throughout five years. As for the creation of the DoD universe in `universe`, we compute `f.Ranking(MktCap()(ascending), top=30)` to indicate that we want our universe to be defined by the thirty firms with highest market capitalization (`ascending` ranking) within the initial universe. The same methodology goes for the factor in `criteria`.

```python
with testcase("Evaluate the performance of the strategy 'Dogs of the Dow'.",
        "See the strategy's overall performance by running it monthly in 2015--2019:"):
    results, df, df0 = q.qrumble("dogs_final:{DATE}/rank/10", "dogs_final:{DATE}/play/10/1y", "jan2015", "5y", periodicity='1m', rebalance = '1y',
                fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05, fee = 0,
```

```
                universe_list=q.universe.fetch,
                universe=lambda f: f.Ranking(MktCap()(ascending), top= 30 ),
                criteria=lambda f: f.Ranking(Yield()(ascending), top= 10 ),
                weight_function=q.mktp_weighted,
                dataframe="both")
    print(results)
```

Listing 5.2: Qrumble's testcase for the Dogs of the Dow strategy for five years in the MKTP.

If we were to have a criteria with multiple factors, like in the Magic Formula, we could sum them as in Listing 5.3.

```
...
criteria=lambda f: f.Ranking(EarningsYield()(ascending) + ROC()(ascending),
    top=30)
...
```

Listing 5.3: Criteria for the Magic Formula in Qrumble.

Each weight scheme has a different associated `weight_function`. It's `q.equal_weighted` for the EWP, `q.value_weighted` for the VWP, `q.mvp_weighted` for the MVP, and for the MKTP is `q.mktp_weighted`.

There are a few disparities of coding when it comes to different investment strategies methods. An example of this would be the Winners and Losers strategy. The DoD only selects assets to buy and hold in the EWP and the VWP, but the WL partakes in short selling, even in those portfolios. Therefore, the testcase for the WL with the EWP looks something like the Listing 5.4. The `RS('6m')` refers to the period on which the relative strength factor (`'RS'`) will take into account, using the price variation over the past six months in this case. As in the WL strategy, the `'winners'` consist of the `top='10%'` of an `ascending` ranking by relative strength and the `'losers'` consist of the `top='10%'` of a `descending` ranking by relative strength.

```
...
        criteria=lambda f: f.Ranking('winners')(RS('6m')(ascending),  top='10%
    ')\
                        .Ranking('losers')(RS('6m')(descending), top='10%'),
            strategy=('buy&hold', 'short'),
            fee=0.0,
...
```

Listing 5.4: Qrumble's testcase for the Winners and Losers strategy for five years in the EWP.

Another possible representation of a different method in Qrumble is the F_score, as displayed further down. In Listing 5.5, we define the universe screening and F_score criteria before the testcase, for simplicity. In the `universe`, we're removing the banking, insurance, real estate, financial, utilities and waste businesses from the initial universe, and from that selecting the `top="20%"` based on the ascending rank book-to-market (`BM`). The `fscore` is exactly composing the F_score as explained in **Chapter 4** as a binary summing system with `astype(int)`. The `ROA` is return on assets, the `OFC` is cash flow from operations, the `ROA_diff` is Δ_ROA and `AccrualRatio()<0).astype(int)` is equivalent to F_ACCRUAL. Afterwards, the `'high'` firms are the ones with scores of `'9'` or `'8'` and the `'low'` firms are the ones with scores of `'0'` or `'1'`, as explained in the previous chapter.

```
def universe(f):

    f.Ranking(BM()(ascending), top="20%")
    return f

def fscore(f):
    profitability = (ROA()>0).astype(int) + (OCF()>0).astype(int) + (ROA_diff()>0).astype(int) + (AccrualRatio()<0).astype(int)
    ...
    f.Ranking('9')(profitability + leverage_liquidity + operating_efficiency, score=9)
    f.Ranking('8')(profitability + leverage_liquidity + operating_efficiency, score=8)
    f.Joining('8', '9', into='high')
    f.Ranking('0')(profitability + leverage_liquidity + operating_efficiency, score=0)
    f.Ranking('1')(profitability + leverage_liquidity + operating_efficiency, score=1)
    f.Joining('0', '1', into='low')
    return f
```

Listing 5.5: Definitions of the universe screening and ranking

Subsequently, we can use the pre-defined universe and F_score criteria directly in the testcase, as shown in Listing 5.6.

```
...
                        universe=universe,
                        criteria=fscore,
                        strategy=('buy&hold', 'short'),
                        fee=0.0,
...
```

Listing 5.6: Universe and criteria within the F_score in Qrumble.

The full listings of examples of each investment strategy executed are presented in Annex I.

# Chapter 6

# Results

In this chapter, we display and discuss the results of the baseline investment strategies exhibited in **Chapter 3**, and three other strategies inspired by researchers' suggestions and ideas. All of these investment procedures were processed yearly in Qrumble, from 2015 to 2019, with the STOXX600 as the main universe, in accordance with our set objectives.

## 6.1 Baseline Strategy Performances

In this section, we evaluate the performance of the unique strategies delivered by Qrumble, as stated in **Chapter 5**. This analysis takes the eight metrics presented in **section 5.2** into consideration, such as return on investment (ROI), mean, standard deviation (St Dev), alpha, yearly VaR and TVaR in percentage and Sharpe and beta.

Broadly speaking, as previously stated in **Chapter 3**, better results can be shown by higher profit metrics, such as ROI, mean, Sharpe and/or alpha, or even by (absolutely) lower risk metrics, including standard deviation, beta, VaR and/or TVaR. Since in most cases there isn't a perfect combination of results according to these various metrics, we use them as a guideline for understanding the potential and favourability of an investment.

The analysis for each strategy goes through a table of the total results after the five years, and a graph representative of the cumulative returns throughout the five years of investment on equities present on the biggest European market. Each table displays the total returns on investments, which includes reinvestment, along with other portfolio evaluation metrics. Every graph showcases the cumulative returns of each portfolio and compares it to the cumulative European market returns, obtained by yearly investments in all stocks present in the index, in a value-weighted portfolio.

Every strategy is made yearly for five years. To this end, there are some tables of results in the Appendix, which are divided in blocks, with each block dedicated to the results solely in each year. For example, the first block is directed to the results after the first year of investment, i.e. after investing in 2015 and gaining possible returns in the beginning of 2016. Each block is independent from the other, in a way that there is no reinvestment of the gained portion into the next yearly investment. For each block, there are results for each of the four types of portfolios we intend to study.

### 6.1.1 Dogs of the Dow

In this subsection, we present and discuss the results of the Dogs of the Dow strategy exhibited by Qrumble, in the European market, from 2015 to 2019.

In the end of the five years of investment, we can observe through Table 6.1 that the VWP was the portfolio that received the highest ROI, mean, Sharpe, beta and alpha, although the results between the first three portfolios didn't differentiate much. The MVP stands out as the portfolio with the lowest standard deviation, and, consequently, lowest VaR and TVaR. On the contrary, the MKTP provided the lowest ROI and the only negative one, mean, Sharpe, and alpha and highest standard deviation, VaR and TVaR. Curiously, the Sharpe value was lower in the portfolios with lower betas, MVP and MKTP, which also received negative alphas. In this case, the attempt of achieving more efficient results with theoretically efficient portfolios was unproductive, specially because the EWP and VWP have similar values of standard deviation, VaR and TVaR to the MVP and a higher ROI and Sharpe.

| Total | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 43.2 (7.45/1y) | 7.97 | 13.93 | **0.62** | 0.88 | -0.56 | 22.35 | 30.58 |
| **VWP** | **44.51 (7.64/1y)** | **8.17** | 14.03 | **0.62** | *0.89* | **0.25** | 21.60 | 30.83 |
| **MVP** | 28.67 (5.17/1y) | 5.82 | **13.42** | 0.48 | 0.7 | -3.05 | **20.72** | **29.95** |
| **MKTP** | *-29.26 (-6.69/1y)* | *2.65* | *43.44* | *0.07* | **0.61** | *-14.63* | *68.59* | *101.82* |

Table 6.1: Total results on the 5-year investment based on Dogs of the Dow strategy.

According to the graph of cumulative returns in Figure 6.1, the market beats any portfolio at the end of the investment, which goes in hand with no Sharpe value higher than 1 in "Total". Even so, there is a brief period where the EWP, VWP and MVP beat the market, between July 2016 and the end of 2017. On another note, the drastic turn in the MKTP is shown in the sudden decrease of cumulative returns in 2016, so much that these never became positive throughout the rest of the investment. Even so, we can see the MKTP recovering since May 2019, which could point torwards a brighter future if the investment had continued for more years.

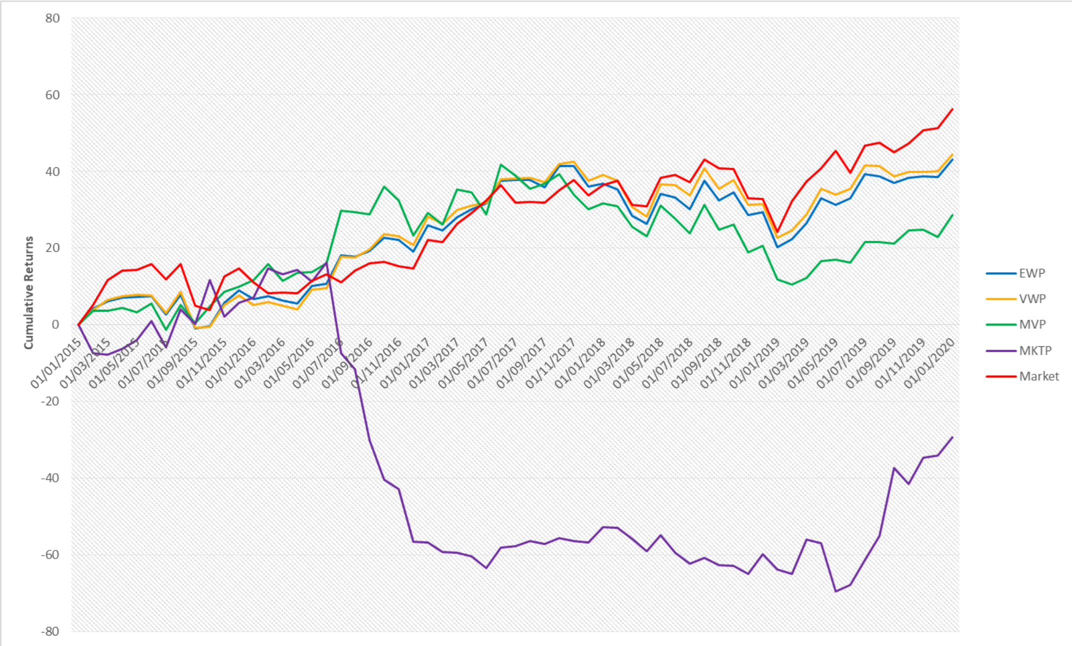


Figure 6.1: Cumulative returns evolution of the Dogs of the Dow strategy.

When looking at the separate years in the Table II.1 present in the Annex II, we can see that the portfolios follow a similar trend between themselves in every metric. For example, ROI increases in 2016, decreases in 2017 and 2018 and increases again in 2019 in every portfolio besides the MKTP, and the same rationale goes to other metrics like mean, Sharpe, alpha. It's interesting to see that in 2016 and 2019, ROI, mean and alpha increased from the past year but the measures for risk, standard deviation, beta, VaR and TVaR, actually decreased for these portfolios, besides MKTP. Additionally, the MVP was the portfolio with the lowest standard deviation, and therefore lowest VaR and TVaR, in two out of five years, which also came through in the "Total". The MKTP suffered great losses in 2016 which had a damaging impact on the overall investment. It is also the portfolio with the highest potential losses every year.

It's evident the DoD didn't succeed in this universe globally, when looking at the low Sharpe ratios and the failure to beat the market on all portfolios.

**Comparison with Existing Research.** Naturally, the cumulative returns of five years of investment wouldn't reach the authors' cumulative returns achievement of 7264% after twenty-six years (O'Higgins & Downes, 2010), but they didn't surpass the reference index of the market. The Sharpe value obtained was also unimpressive, being lower than 1.

When looking for other studies employing this strategy, the outcomes exhibited significant disparities, which does not inspire much confidence in the likelihood of success. Bruce and Bhabra (2006) experimented intensely within the New Zealand market, with the NZSE Gross Index, and received negative results from 1992 and 2002 of yearly and two-year investments, both on the EWP and VWP. They suspected the illiquidity of stocks and poor price momentum was what contributed to those results, since New Zealand's stock market is full of high dividend yields and there is no assymetry in taxes between capital gains and dividend income.

On the other side, Rinne and Vähämaa (2011) tested the DoD's usual yearly selection with no fees for EWPs on the Finnish market through the OMXH25 index, over the period from 1988 until 2008, and experienced overall satisfying results. The cumulative returns consistently outperformed the market index, which was about 817% at the end of twenty-one years of investment, although they argue that "the positive DoD premium is not necessarily large enough to survive transaction costs and taxes" (Rinne & Vähämaa, 2011). They also acquired an average Sharpe of 0.589, which was a result of higher Sharpe ratios than the market index for fourteen years. Their beta estimate was about 0.98, which is not very far from the simple portfolios' betas we obtained. The fact that the our Sharpe value was slightly higher than the ones from the Finnish study, leaves suspicion whether the investment would benefit from more years, since there is a big jump from five to twenty-one years.

### 6.1.2 Buying Winners and Selling Losers

Within this subsection, we showcase and analyse the outcomes of the Buying Winners and Selling Losers strategy as implemented by Qrumble in the European market during the years 2015 to 2019.

As the 5-year investment period concludes, we can see through Table 6.2 that the MVP achieved a much higher ROI than the other portfolios, followed by a higher mean, Sharpe, alpha, and lower standard deviation, VaR and TVaR. Its beta value doesn't correlate to the most market influenced portfolio since the MKTP's beta is absolutely higher. Despite being the highest positive beta, it remains relatively median as it is still 0.5. In this sense, the MVP proved to be more efficient and was able to show better results overall while choosing itself the assets to buy and sell. On the other hand, the MKTP provides the worst result as it obtains the lowest ROI, mean, Sharpe and alpha and highest absolute values in all risk measures. In this scenario, it is clear that each portfolio has very different terminal results in every metric, in a way that this strategy was sensible to different weights, specially on the VWP and MKTP. The MKTP resulted in a unlucky turn of events, which can happen with high levels of risk/exposure. On a different note, the big disparity in results between the EWP and VWP suggest that the EWP minimized the price oscillations in a way that the VWP wasn't capable of doing, since the EWP is the only other portfolio that buys and sells the same assets as the VWP. This comes to show that bigger companies didn't perform as expected. Either the big winners didn't rise or fell through, and/or the big losers recovered and increased in price fast enough within six months.

| Total | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 12.16 (2.32/1y) | 3.4 | 17.0 | 0.24 | **0.06** | 15.03 | 26.68 | 38.02 |
| **VWP** | -13.65 (-2.89/1y) | -1.07 | 17.25 | -0.03 | -0.2 | 4.86 | 26.01 | 40.3 |
| **MVP** | **47.32 (8.06/1y)** | **8.24** | **14.14** | **0.63** | 0.5 | **18.96** | **22.32** | **32.02** |
| **MKTP** | *-321.37 (-217.22/1y)* | *-169.88* | *1319.32* | *-0.13* | *-3.63* | *-695.71* | *369.69* | *1373.6* |

Table 6.2: Total results on the 5-year investment based on Buying Winners and Selling Losers strategy.

When looking at the graph present in Figure 6.2, it's apparent that it's challenging for any portfolio to beat the market, when in fact only the MVP showed some hopes in outperforming the benchmark, doing so from September 2015 to November 2016 and in the end of 2018. The MKTP also beats the market for a short period in the beginning of the investment but is followed by drastic decreases in 2015, 2017 and 2019. In the end of 2019, we can see that the MVP is rising, almost reaching the market and the MKTP increasing.

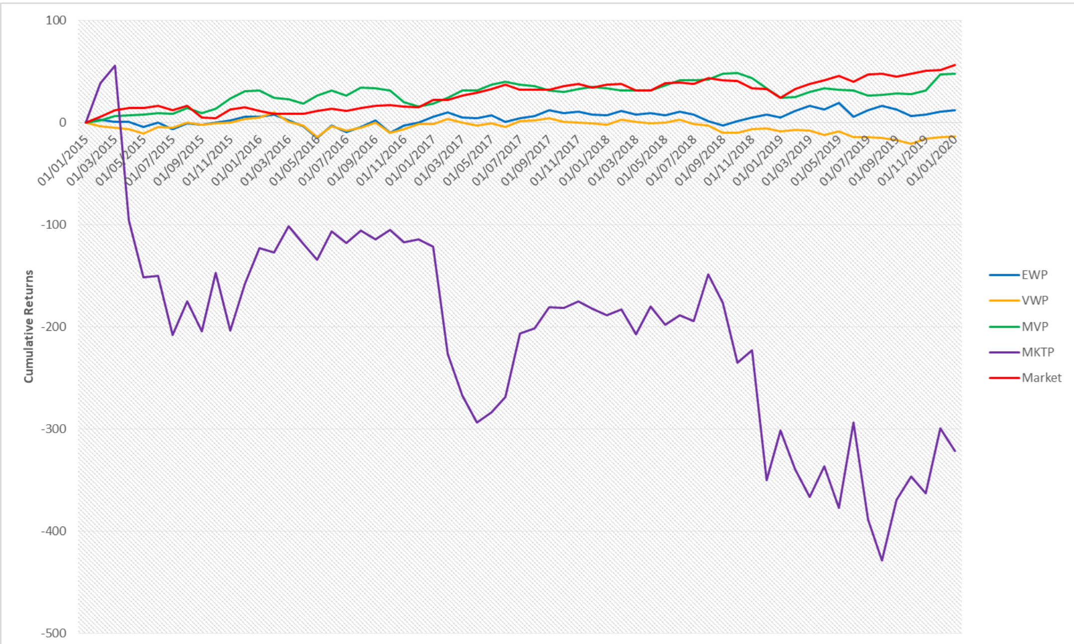


Figure 6.2: Cumulative returns evolution of the Buying Winners and Selling Losers strategy.

This strategy seems consistent throughout the years, in the way the same portfolios achieve highs and lows in ROI and standard deviation similarly in most years in the Table II.2 in Annex II. An interesting take away is that the EWP achieves better ROIs, means and standard deviations than the VWP year after year, which goes in hand with the idea of better weighting by the EWP mentioned before. Unlike the VWP, the EWP gave more weights and importance to the smaller companies and it paid off in slightly better results. The MKTP obtained the lowest ROI and Sharpe in every year besides 2016 and 2018, and had the highest mean in 2019. The MVP got the lowest standard deviation and consequently, lowest VaR and TVaR very frequently. The MVP also achieved the best ROI and mean and lowest standard deviation in 2015, 2017 and 2018. Another compelling occurrence was that only the MVP accomplished a Sharpe surpassing 1, an occasion that even occurred three times. On another note, something else that struck as odd in this situation was the MKTP in 2018 and 2019, where it got a negative ROI and a very high mean of returns. This probably happened because the ROI only counts the gains, or losses, at the end of each six months.

It's clear that the results were unsatisfactory with no portfolio exceeding the benchmark and the Sharpe ratio not being very high. Even though the MVP fulfilled its purpose effectively, it wasn't enough. As in the DoD, a possible explanation for this is the short period we're experimenting on, though this momentum investment strategy is supposed to focus on the short-term.

**Perturbances in the Market Portfolio.** As we can observe in Table II.2 in Annex II, there are some unusual performances in the market portfolio. Here, we select an example and seek to explain the logic behind this.

A situation of disparity in Table II.2 can be the market portfolio in 2019, where it got a negative ROI of −78.63% and a mean of returns of 289.93%. When observing the results delivered by Qrumble in Listing I.9 in Annex I, we can see that the daily returns are very different from one another, creating a high standard deviation, particularly of 275.62%. Nonetheless, in April 18th and April 23rd, the daily returns were 99.63% and 97.24% respectively. This happened because the portfolio value was very close to zero in those dates. To be more specific, if we calculate the daily return of April 18th by the ROI's in April 17th and April 18th, we obtain

$$\frac{(1-0.9705)-(1-0.9852)}{(1-0.9852)} \simeq 99\%,$$

which is a very large daily return compared to the others. This happened because the denominator in the calculation of the daily return is too close to zero, making the result exponentially high and portfolio return approaching -100%. The mean of daily returns was approximately 1.151%, and therefore the annual mean is that times 252, which is 289.93%.

On another hand, the ROI is the percentual difference between the first day and last day of investment, and it was caught in a time of decrease in prices, ending up negative.

**Comparison with Prior Studies.** Whilst comparing these results with the pioneering study by Jegadeesh and Titman (1993), we can state that our results results didn't attain the level of success that theirs did. Neither of our portfolios were able to come close to an annual average compounded excess return of 12.01%, which can be understandable since this profit was possible after a longer time of investment, from 1965 to 1989. Interestingly enough, the authors obtained significant betas (mostly higher than 1) and agreed to prioritize low betas as they experimented with low, median and high beta selection and received better results with low beta stocks. "This is because the relative strength strategy tends to select high- (low-) beta stocks following a market increase (decrease) and hence tends to perform poorly during market reversals" (Jegadeesh & Titman, 1993).

After an intense research of available studies on momentum strategies based on relative strength, the paper created by Narayan et al. (2017) tested the WL strategy on the Indian market (CNX 500 index) from July 1992 to December 2014 with a 6-month hold with a month pause between different holdings. While the annualized returns of the market were 9.12%, the WL profits turned out to be 22.56% for EWPs and 16.92% for VWPs, both annually. Moreover, EWPs provided abnormal returns with an alpha of 11.76% and the contrary happens with the VWP, which got a statistically insignificant alpha. Clearly, no portfolio from our experience came even close to those results, despite of having high alphas in the EWP and MVP.

### 6.1.3 F_score

This subsection is dedicated to presenting and examining the results of Qrumble's application of the F_score strategy in the European market between 2015 and 2019.

When the 5-year investment period culminates, we can observe through Table 6.3 that the MVP accomplished a higher Sharpe ratio and lower results in all risk metrics. On the other hand, although the MKTP had a much highest ROI and mean, it also had the highest risk metric values, leading to a weak Sharpe and high possible yearly losses. At first, it seems that the different weighting didn't create much disparity in the first three portfolios, but the results in MKTP were very divergent. As in the prior section about WL, the MVP was competent in its function, since it turned out to be a better weighting scheme in terms of overall risk.

| Total | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 73.44 (11.64/1y) | 12.58 | 19.19 | 0.69 | 0.94 | 20.31 | 31.71 | 41.29 |
| **VWP** | *72.96 (11.58/1y)* | 12.6 | 19.57 | 0.67 | 1.11 | *12.26* | 30.99 | 43.31 |
| **MVP** | 76.19 (11.99/1y) | *12.55* | **17.31** | **0.76** | **0.92** | 20.97 | **26.21** | **38.95** |
| **MKTP** | **576.49 (46.57/1y)** | **148.6** | *269.54* | *0.55* | *2.73* | **632.68** | *223.40* | *545.74* |

Table 6.3: Total results on the 5-year investment based on F_score strategy.

Upon examining the graph in Figure 6.3, the portfolio that stands out the most is the MKTP, with exponentially high results and consistent outperformance, after its negative turmoil in the first trimester of 2016. The drastic -400% decline in accumulated returns during 2016 within the MKTP might have been influenced by potential disruptions in the market portfolio (as explored in section 6.1.2). Additionally, the use of short-selling coupled with leveraged investment strategies could have potentially enhanced this decline. This matter deserves further investigation and should be a focal point for future analysis.

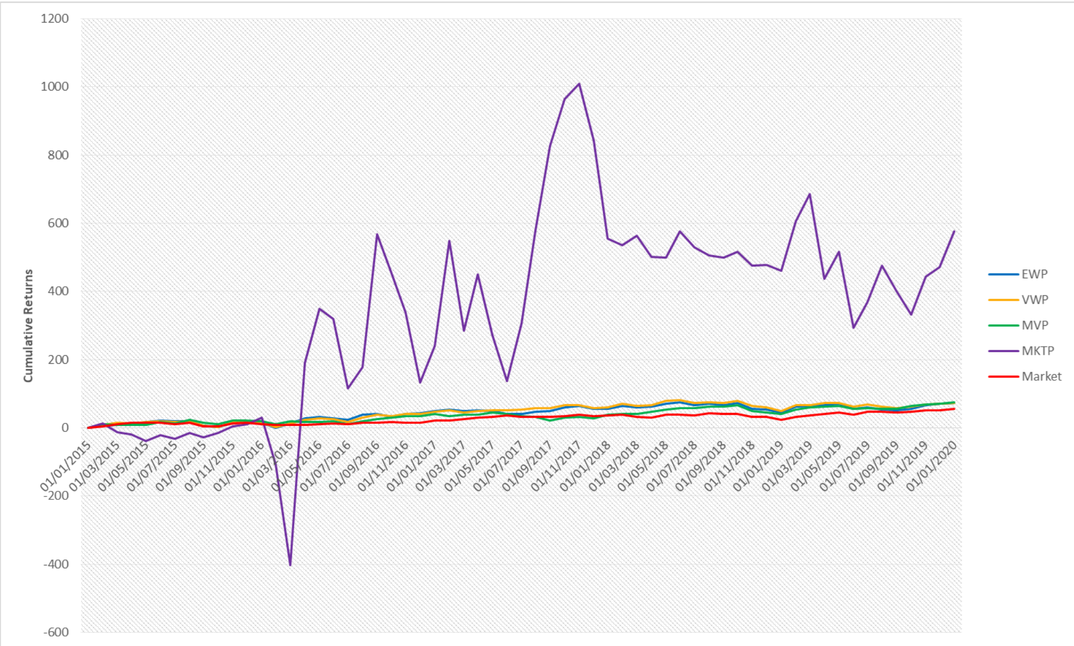


Figure 6.3: Cumulative returns evolution of the F_score strategy in all portfolios.

We can observe the other portfolios removing the MKTP of the graph for a closer look, in Figure 6.4. Here, we can see clearly that every portfolio surpasses the benchmark. The EWP and VWP seem to have an analogous trend, and follow the market movements, being below it in two short period of time. The MVP only was under the benchmark from August 2017 and January 2018.

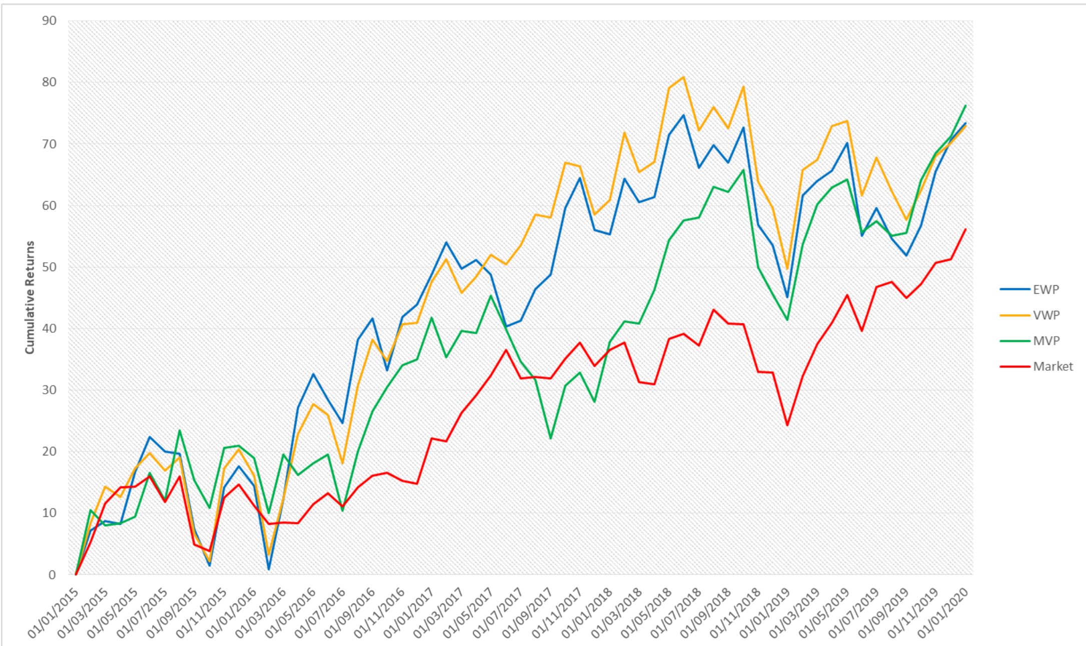


Figure 6.4: Cumulative returns evolution of the F_score strategy without the MKTP.

As seen in the Table II.3, the MVP was the portfolio that acquired the lowest standard deviation, in the last four years. It was also the only portfolio that "survived" in 2018, by not getting to negative levels of ROI, mean and Sharpe. It has also achieved generally lower VaR and TVaR, due to lower risk, and an absolutely low or median beta. On another note, the EWP and VWP displayed parallel behaviours in increases and decreases on most metrics, which counterbalances the contrarian movement of MVP in 2018 in profit metrics. The MKTP seems to follow that trend in most metrics but in an exponential way due to more risk exposure.

Overall, it was interesting to see that every portfolio succeded in beating the market, even with Sharpe ratios below 1, which we're trying to avoid. Despite of the mediocre Sharpe ratio and high values of VaR and TVaR, one could be tempted to use the MKTP for its extremely high ROI.

**Comparison with Previous Literature.** When comparing our results to the original investment strategy, the average annual return of Piotroski (2000) was about 23% for the exactly same strategy, but from 1976 to 1996. Although our results didn't reach that average return per year, it can be said that they came close to enjoying similar success by observing the satisfactory high values of profit metrics. Our MKTP was the only portfolio that had a larger average return per year.

On a comparative study by Jahan et al. (2016) between Piotroski's model and other important value investing models, such as Graham's, they secured analogous outcomes for returns. This paper conducted various experiments on equally weighted portfolios, using different combinations of screening rules and ranking systems on the S&P 500 from January 1999 to December 2014. The average annualized return was about 16.43% with a standard deviation of 21.62% and an average beta of 0.60. Since the study wasn't directed towards the efficiency of Piotroski's method, but the other possible combinations, there isn't much more valuable information for comparison. All of our beta values were above theirs, but our standard deviation was slightly lower, excluding the MKTP. Concerning the MKTP, it was the only portfolio to exceed their average annualized return, along with a huge amount of risk.

Domingues et al. (2022) conducted a paper about experiments and consultation on three value investment strategies on the Brazilian market (Ibovespa) for the period of January 2006 to December 2019, one of those being two variations of this strategy. Firstly, the BM was set to choose the two top quintiles regarding this factor, and from there selecting companies with a score higher of 7 to buy, with no losers in mind to sell. This experience provided an annualized return of 30.06% with Ibovespa's at 9.26%, an alpha of 4.83% and beta of 0.58 which indicates low exposure to market risk. Clearly, not even our best results came close to the annualized return, but achieved a higher alpha. In terms of beta and annualized return, we can make the same comments as in the comparison in the previous paragraph.

A paper produced by Hyde (2018) sougth to apply this strategy within the Australian Stock Exchange (S&P/ASX 200), using month-end data from January 1992 to December

2013. To this end, there were various studies and tests on different time and weight approaches of the buy-and-hold strategy. Firstly, in a previous selection of the top quintile of value stocks measured by book-to-price ratio (or book-to-market), and a a long/short technique, in buying shares with F_scores ≥ 7 and selling F_scores ≤ 2. For examining the firm size effect in this strategy, they conducted 6-month hold investments in EWPs and VWPs in the 200 biggest companies and the 300 smallest ones. The tests provided better results for the small-cap companies, with an average return of 2% per month (pm) on the EWP and 1.36% pm on the VWP and as for the big firms, they got an average monthly return of 1.09% for the EWP and 0.85% fo the VWP. Although we can't directly compare our annualized average returns to their monthly average ones on big and small-cap firms, we can deduce we had the same effect on the simple portfolios weighting scheme, our EWP did slightly better than the VWP. Furthermore, in an analysis of the potential drive in high F-score stocks' premium by size effect, there were results that concluded that premium evidently relies on the portfolio weighting scheme, like an alpha of 1.31% pm for an equal-weighted portfolio with a 12-month hold and one of 0.52% pm for index-weighted returns. In our results, we experienced somewhat similar results, since the ROI, Sharpe and alpha is slightly larger on the EWP. Hyde (2018) stated that the application of the F-score on its own is undesirable by most of investors, becoming more appealing subject to a combination of commonly employed factors such as momentum, value and low risk signals. In spite of the this paper not being the best for comparisons, it was inspiring for improving this strategy with other factors, different market regimes and/or variations of weights in portfolios (Hyde, 2018).

Aggregating studies similar to ours regarding this exact method, proved to be challenging. Many of the available studies deviate by modifying the initial fundamental factor (BM), and/or classify the winner and loser assets with different scores.

### 6.1.4 Magic Formula

Here in this subsection, we unveil and dissect the results of Qrumble's application of the Magic Formula strategy in the European market throughout the period spanning 2015 to 2019.

When analising the Table 6.4, we can see that the MKTP acquired the highest results in every metric besides the Sharpe value, which was the highest in the VWP. In contrast, the EWP obtained the lowest results in ROI, mean, Sharpe and alpha. Once again, the MVP succeeded in having the absolute lowest values in all risk measures. When looking at the first three portfolios, there aren't many disparities noticeable, specially on the mean and standard deviation and VaR and TVaR between the EWP and MVP. As for the other theoretically efficient portfolio, the MKTP succeeded in exhibiting a plausible lucky turn of events as a proxy for higher risk, not only due to its elevated ROI, mean and alpha but also higher Sharpe ratio than EWP and MVP.

| Total | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | *44.77 (7.68/1y)* | *8.22* | 14.17 | *0.62* | 0.93 | *-1.24* | 22.54 | 33.39 |
| **VWP** | 69.22 (11.09/1y) | 11.26 | 14.10 | **0.84** | 0.89 | 16.01 | 22.36 | 31.73 |
| **MVP** | 48.66 (8.25/1y) | 8.69 | **13.81** | 0.67 | **0.65** | 14.16 | **21.36** | **30.46** |
| **MKTP** | **373.03 (36.45/1y)** | **62.36** | *80.59* | 0.78 | *1.3* | **258.27** | *114.51* | *182.09* |

Table 6.4: Total results on the 5-year investment based on the Magic Formula strategy.

The graph in Figure 6.5 presents some more positive findings. It's apparent that the MKTP provides outstanding cumulative returns, becoming exponentially high after 2016 without any hint of withdrawing besides some usual and inconsequential irregularities. Additionally, it's worth noting that the VWP was the second most consistent portfolio that beat the market since April 2016. The other two portfolios proved to be inefficient on surpassing the benchmark.

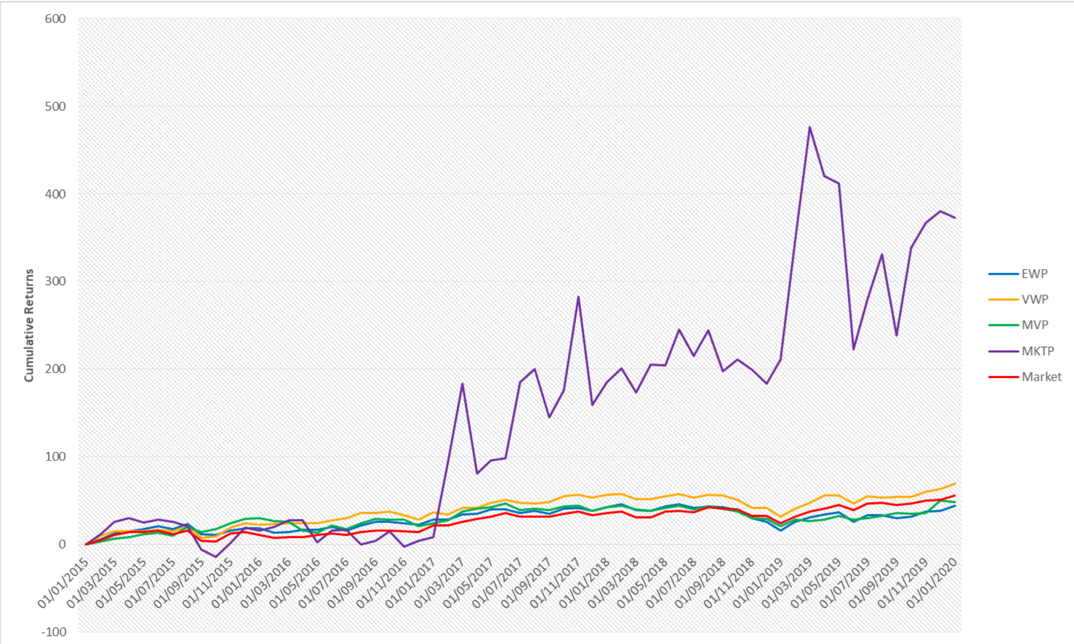


Figure 6.5: Cumulative returns evolution of the Magic Formula strategy.

Throughout the 5-year investment, there are some interesting revelations within this strategy, and we can observe more in the Table II.4 available in the Annex II. The MVP is the portfolio that achieves the lowest VaR and TVaR most years. On the other hand, every portfolio has moments on which they present a Sharpe higher than 1 and it's not reflected on the "Total" section, which suggests that the drastic event in 2018 was strong enough to prevent a better Sharpe in the end. When looking at the profit metrics, there are some recurring patterns happening in every portfolio such as decreases in 2016 and 2018 and decreases in 2017 and 2019, particularly drastic ones on the MKTP. On the reverse side, there are no similar patterns of risk metrics between the various portfolios.

After this analysis, one could be divided between the VWP and MKTP. Even though the VWP achieved overall good results and beat the market, the MKTP excelled like never before witnessed. Its exponentially high ROI, annualized and mean came along with high amounts of risk per usual, but it's not as much as expected, specially after observing the other investment strategies' results. This portfolio was even the only one in the MF experiment to "survive" the 2018 market crash, which can also bring a sense of safety.

**Comparison with Related Research.** As mentioned above, the original experiment in the S&P500 from 1988 to 2004 by Greenblatt (2006) resulted in an annualized average return of 30.8% with the market at 12.3%. As anticipated, most of our portfolios didn't meet this achievement, but the MKTP did.

The same paper conducted by Domingues et al. (2022) explored the MF. They created an analog model of the MF for the Brazilian market by working with return on invested capital (ROIC) instead of ROA and with the exclusion of firms with market value less than R$ 160 million and a minimum ROIC level of 20%. In the end, the average annualized return for the equal-weighted portfolio was 21.92%, in contrast to Ibovespa's 9.26%. The portfolio generated an alpha of 2.68% per annum and carries less risk than the market, with a beta of 0.91. We can state that the VWP had a similar beta and deduce that it had a slightly higher alpha, but its mean was below the comparative result. On the other hand, the MKTP surpassed this result with basically the three times of the annualized average return of their result and a much higher alpha, even by having more systematic risk with its beta above 1.

Another study that developed interest and inspiration later on, by Davydov et al. (2016), was about applying the MF and some variations to it on the Finnish market (OMXH CAP GI) from 1991 to 2013, on equal-weighted portfolios. In this case, the original MF achieved and annual average return of 19.3% and the market 13.6%, with a Sharpe of 0.641, alpha of 6.71% and beta of 0.741. Comparing these results with the VWP, the portfolio with the highest Sharpe had a lower annualized return, slightly higher beta and a higher alpha. About the MKTP, the idea presented on the last paragraph also applies here. This study proved to be deeply rich in metrics and inspirational afterwards in the next section.

### 6.1.5 Market Downfall in 2018

In each and every baseline strategy tested on the European market from 2015 to 2019, it is apparent that there was some kind of a turmoil in 2018, since they all dealt with underperforming or negative outcomes. To comprehend better how this happened, we've analysed the weights and prices oscillation in 2017 and 2018 of the selected equities in the DoD, for being the baseline strategy with the fewest assets to analyse on average, making it easier to observe each one. We've also investigated potential macroeconomic variables in 2018.

**Dogs of the Dow in 2018.** In the Table 6.5 presents the price variations of each asset chosen by the DoD in 2018. We can also assess their weights in the VWP, MVP and MKTP, knowing that in the EWP their weights were 10% each. The price oscillation in 2017 is also shown, due to their importance and usage in the weight selection in the theoretical portfolios.

| Company | Price Variation in 2017 % | Price Variation in 2018 % | VWP Weight % | MVP Weight % | MKTP Weight % |
|---|---|---|---|---|---|
| **VOD.L** | 22.48 | -29.26 | 7.2 | 19.2 | 43.2 |
| **BP.L** | 6.83 | 1.46 | 11.9 | -7.6 | 9.3 |
| **HSBA.L** | 21.61 | -10.84 | 17.9 | 15.1 | 21.3 |
| **AZN.L** | 20.66 | 19.68 | 7.5 | 3.2 | 23.8 |
| **ALV.DE** | 28.02 | -5.29 | 8.7 | 7.9 | 112.9 |
| **FP.PA** | -0.47 | 5.36 | 11.9 | 29.6 | -45.3 |
| **INGA.AS** | 18.7 | -35.54 | 6.1 | -0.5 | 9.3 |
| **BATS.L** | 11.85 | -46.32 | 13.2 | 7.7 | 5.1 |
| **DAI.DE** | 3.88 | -31.4 | 7.2 | 21 | -23.6 |
| **SAN.PA** | -3.25 | 11.9 | 8.4 | 4.4 | -56.1 |

Table 6.5: Price variations and different portfolio weights on the assets chosen by the DoD in 2018.

The negative mean and ROI across all portfolios in 2018 imply that, in general, the acquired stocks witnessed a decrease in price. This has been verified, as most of the shares bought in 2018 have fallen in price. In particular, BATS.L, INGA.AS, DAI.DE, VOD.L, HSBA.L and ALV.DE fell by 46.32%, 35.54%, 31.4%, 29.26%, 10.84% and 5.29% respectively. The remaining companies increased their price to a small extent, as presented in Table 6.5.

In the EWP, with exactly equal weight distribution, the price decreases were so drastic that made the portfolio outcome negative. However, the MVP and MKTP could have potentially avoided this issue if the prices of the "unlucky" stocks had exhibited similar behavior in 2018 to the 2017 prices. Companies that experienced a price rise in 2017 and a fall in 2018, such as HBSA.L with a 21.61% decrease, BATS.L with an 11.85% rise or VOD.L with a 22.48% rise, or even companies that underwent more unimpactful changes such as DAI.DE with a 3.88% rise in 2017, contributed to the "deception" of the portfolios optimized for efficiency, considering the prices of the preceding year.

Ironically, the portfolios highlighted in the previous paragraph in an explanatory assumption were in fact the stocks with the highest weights for buy and hold in the MVP. More specifically, DAI.DE had a weight of 20.99%, VOD.L 19.15%, HBSA.L 15.13% and BATS.L 7.75%. The beta of this portfolio was 0.99, so the portfolio suffered practically the same as the market did.

In MKTP, the weights were approximately -23.57% for DAI.DE, 43.18% for VOD.L, 21.33% for HBSA.L and 5.09% for BATS.L, for the companies mentioned above. In addition, the stock with the most influence was ALV.DE with a weight of 112.94%, which also experienced a 28.02% rise in 2017 and a 5.29% fall in 2018. In this portfolio, the beta was 1.32, so the portfolio suffered even more influences than the market, leading to an even greater drop in ROI and mean than the other portfolios.

In the VWP, the weighting was more evenly distributed than in the previous two portfolios. There was one stock that commanded more of the portfolio's value (HSBA.L with 17.9%), but the weightings didn't differ much since they're all between 6.1% and 17.9%. So the procedure and rationale is very similar to the EWP.

**Macroeconomic Influences.** According to a Washington Post article by Rabinowitz and Shapiro (2018), the U.S. market has had a consistent upward movement since the recession in 2009, but started to experience downturns early in 2018 and throughout the year. Several catalysts that played a role in this collapse included the ongoing trade war between the United States and China, rising of interest rates and high rates of volatility mostly by uncertainty in government policy.

In the beginning of the year, tariffs on imports such as solar panels, steel, washing-machines and aluminum were imposed by the U.S., which was followed by China's response on tariffs on over $5 billion worth of U.S. goods. More accusations, retaliations, tariffs and practices carried this economic tug of war, such as an unfair trade for intellectual and technological property by China and retreat of a possible truce by the Trump administration (Bown & Kolb, 2023). The continuing trade war has contributed to a ceaseless market movement and unpredictability.

The Federal Reserve had also declared a rise on the interest rate four times during 2018. These increases meant higher borrowing costs and opportunities to control inflation. An additional concern was that the benchmark at the time was already low and combating a potential recession could be constrained. Furthermore, the world's major central banks, including the Federal Reserve, had been implementing tighter monetary policies, which increases difficulty in accessing loans or credits and diminishes liquidity in the market overall, two important factors that could impend global economic growth (Frazee, 2018).

Alongside this, 2018 was marked by unstable market dynamics and uncertainty creates a tendency in businesses to less hiring and investment in equipment, innovations and people, which are essential for long-term economic growth. This uncertainty is usually measured by the volatility index, which estimates the variation of options for the S&P 500 over a thirty day period. It is believed that Trump's comeback on the market turmoil by pondering the removal of both the chairman and the treasury secretary of the Federal Reserve also caused ambivalence on government policies and the market (Dam, 2021).

> "When the U.S. sneezes everyone else catches a cold." – Jasper Lawler (Beswick, 2018)

It is clear that any turbulence from two of the biggest economies ricocheted into other markets, including the European one. But apart from this, Europe also had to deal with United Kingdom's Brexit, budget crises in Italy, economic woes in Germany, social issues in France, etc (Martin, 2018).

More specifically, the unpredictability of the turn of events involving Brexit made it problematic to forecast the market and the "Brexit referendum phase depressed UK–EU trade by around 10.5%" (Buigut & Kapar, 2023). There was a shift from low volatility, outperformance by equities and high liquidity to the contrary, and even the return of bear period. The European Union had agreed a deal with Italy to establish a budget and consequently averting a long-expected crisis in the eurozone, but Italy's government was still euroscepticist and volatile. Germany, the country that has been the economic epicenter of Europe, experienced fragility and deceleration of growth. This was due to competition, inability for automakers to adapt to sustainability goals, and many other factors. Protests and unresolved problems in France damaged the French economy, specially in tourism-related shares (Martin, 2018).

## 6.2 Creating Investment Strategies

In this section, new multi-factor based strategies have been developed, drawing inspiration from ideas suggested by academics who analysed the baseline unique strategies we focused early on. The evaluation of portfolio and table and graph design is executed similarly to the one in the previous section.

### 6.2.1 Liquid Median Dogs of the Dow

**Motivation.** One intriguing work around the Dogs of the Dow strategy is one paper with the intention of trying this method in the New Zealand market by Bruce and Bhabra (2006). Interestingly, with high hopes of this approach in a market characterized by high dividend yields and no asymmetry in taxation between capital gains and dividend income, they've obtained negative results of constant underperformance on an absolute and risk-adjusted basis, contrasting with the relative success in various international markets. As mentioned previously in section 5.1.1, they used monthly data of the NSZE Gross Index from 1992 to 2002 for the creation of portfolios according to DoD yearly. Like so, there was not underperformance comparing to the market index in New Zealand only in one year of the 11 one-year holding periods in value-weighted portfolios, with worse performances for longer holding periods, as 3 and 5 years. On the other hand, equal-weighted portfolios had the chance to give more weight to small capitalization stocks, which improved the performance in the years of small stocks inclusion, with outperformance in 3 out of 11 years. For a more direct comparison, they found that a portfolio containing five small firms (small market capitalization) outperformed significantly the portfolio containing five stocks of large businesses in the most recent 5 years out of 11 holding-periods and they even outperfomed the NZSE Gross Index in 3 of those outstanding 5 years. Within this separation and further examination, the poor performance of large capitalization stocks goes in hand with a sustained downward price movement since the year prior of the investment. With value and price momentum having an inverse relationship (see Asness (1997)) and the illiquidity of stocks trading on the NZ market, these big high-yield firms didn't benefit from the goal the Dogs of the Dow projects (Bruce & Bhabra, 2006).

This paper served as a source of inspiration for improving this contrarian method. It fulfilled this by considering market capitalization adjustments and incorporating the liquidity factor, a concept utilized by Piotroski (2000). Let us refer to this strategy as Liquid Median Dogs of the Dow.

**Methodology.** The approach of this investment strategy is simple. We chose to incorporate somewhat small cap stocks by aiming to approach the median range of the index, even though the STOXX600 is already made of very high market capitalization companies by nature. I conducted an initial screening of the universe to the bottom 50% companies based of market cap and afterwards selecting the top 20% of those companies based on the same factor. Subsequently, we introduced the liquidity factor emphasized by Piotroski (2000), by creating a score based on top dividend yield and top liquidity, selecting ten companies in total. The fusion of these two fundamental factors is created as the MF suggests, in a way that both of these factors have the same importance in selecting the ten assets.

**Results.** In this segment, we offer results insights into the performance of Qrumble's Liquid Median Dogs of the Dow strategy in the European market from 2015 to 2019.

When taking a glimpse at the Table 6.6, we can observe that the VWP achieved the highest ROI, mean, Sharpe and beta and lowest standard deviation, VaR and TVaR. The EWP also performed well in a way that had results close to the VWP. Still, the other portfolios didn't receive such benefit from this investment approach. An example of this is the negative ROI of the MKTP and the low values of Sharpe in both holdings. Even so, it's interesting the fact that the MKTP was portfolio with the lowest absolute beta.

| **Total** | **ROI % (annual)** | **Mean %** | **St Dev %** | **Sharpe** | **Beta** | **Alpha %** | **VaR/1y %** | **TVaR/1y %** |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 118.58 (16.93/1y) | 16.34 | **14.73** | 1.15 | *0.9* | 41.49 | 22.29 | 33.15 |
| **VWP** | **123.14 (17.41/1y)** | **16.74** | **14.73** | **1.18** | *0.9* | 43.5 | **22.16** | **33.07** |
| **MVP** | 31.55 (5.64/1y) | *6.49* | 15.07 | 0.47 | 0.72 | *-0.2* | 22.18 | 34.41 |
| **MKTP** | *-8.35 (-1.73/1y)* | 13.89 | *55.72* | *0.26* | **0.55** | **45.48** | *76.42* | *136.52* |

Table 6.6: Total results on the 5-year investment based on Liquid Median Dogs of the Dow strategy.

The graph in Figure 6.6 shows that the VWP and EWP beat the market in all five years of investment in that particular order and are the only ones to do so, as expected. On the flip side, the MVP stays under the benchmark and the MKTP presents big turmoils in sudden outperformances, being mostly under the benchmark too.

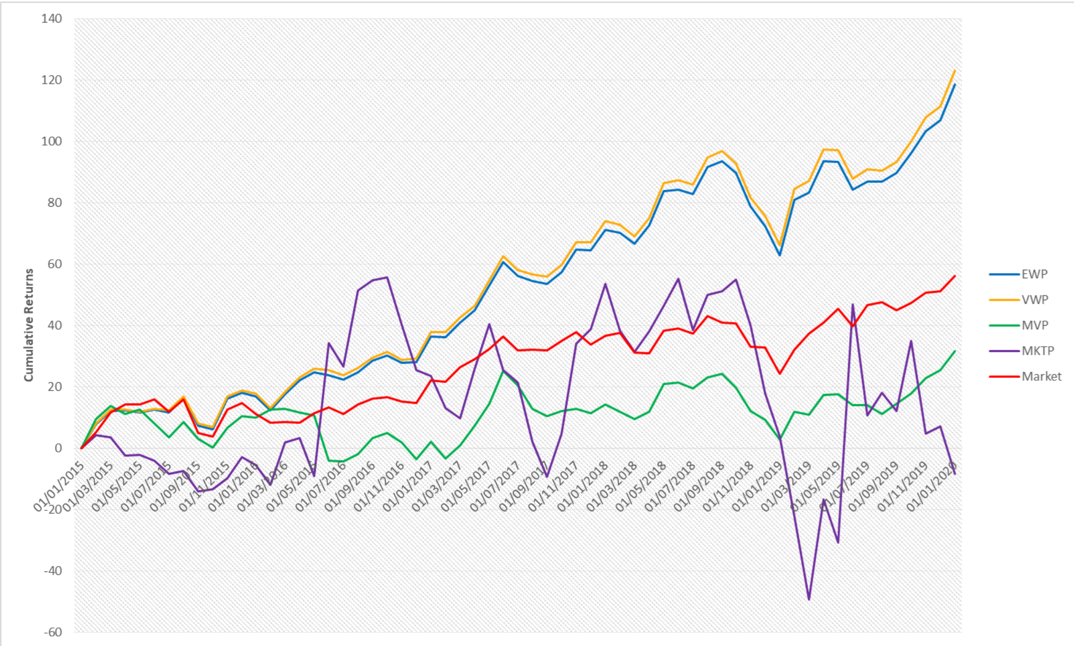


Figure 6.6: Cumulative returns evolution of the Liquid Median Dogs of the Dow.

Throughout the 5 years of investment, we can observe through Table II.5 in the Annex II, that the high Sharpe values attained by the EWP and VWP in four years stand out, both transcending 2 in two years. Both the EWP and MVP presented the lowest standard deviation two times. Despite of the MVP not fulfilling its goal as the theoretical efficient portfolio with lowest variance, it was still the portfolio with the lowest absolute beta in most cases. This comes to show that, maybe, a slightly lower beta won't show much progress as expected, but those results are also dependent on other factors.

For a deeper analysis of the influence of each modification of the DoD, the Table 6.7 displays the changes of metrics on a 5-year investment with each alteration of the DoD that lead to the idea displayed. Firstly, the initial change in DoD experimented was reverting the ranking by the market capital factor, which didn't live to the expectation of a strong size effect and was ineffective in every metric, comparing with the original DoD. Like so, in order not to be so drastic, we've tried a sort of median market capital and it proved to be very impressive. It had the exact opposite behaviour and results than the experiment before, by having better values than the DoD in every metric taken into consideration. Subsequently, the plan persisted on being the influence the liquidity factor could have on the DoD and whether the best placement of the market capital selection could also benefit from that. Thus, we tested the DoD with the liquidity factor (Liquid DoD) and obtained better results than the original investment strategy. Even so, when adding this two modifications together, the investment strategy didn't end up to be the "best of the best" within this experience. Then, in a sense to verify the ineffectiveness of the small cap firms theory, we've reverted the market capital rank on the Liquid DoD, worsening the results of this strategy in every metric. The usage of small-firms in the Liquid DoD emerged as the poorest-performing investment strategy experiment in this collective of alterations of the DoD. On the flip side, the median DoD received astonishing results when compared to the original strategy, and finest profit outcomes on the VWP overall. Interestingly, the Liquid DoD accomplished the best results according to risk, mostly on the VWP.

When comparing the final results with the baseline strategy DoD, Table 6.7 also showcases that the changes provided a great advantage to the simplest portfolios, EWP and VWP. Not only the ROI and mean exceeded the previous outcomes by more than 2.5 times, but the risk metrics had an almost insignificant increase, resulting in a successful experience. The graph in Figure 6.6 also corroborates the effectiveness of this blended strategy, as the EWP and VWP remain consistently above the benchmark.

| DoD | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 43.2 (7.45/1y) | 7.97 | 13.93 | 0.62 | 0.88 | -0.56 | 22.35 | 30.58 |
| **VWP** | 44.51 (7.64/1y) | 8.17 | 14.03 | 0.62 | 0.89 | 0.25 | 21.60 | 30.83 |
| **DoD w/ min MKt Cap** | | | | | | | | |
| **EWP** | 27.9 (5.04/1y) | 6.09 | 16.05 | 0.42 | 0.91 | -11.49 | 24.68 | 37.73 |
| **VWP** | 26.44 (4.8/1y) | 5.87 | 16.05 | 0.4 | 0.91 | -12.68 | 24.53 | 37.8 |
| **DoD w/ median Mkt Cap** | | | | | | | | |
| **EWP** | 135.39 (18.68/1y) | 17.72 | 14.28 | 1.28 | 0.87 | 49.88 | 21.3 | 31.12 |
| **VWP** | **136.85 (18.82/1y)** | **17.84** | 14.23 | **1.3** | 0.87 | **50.66** | 20.88 | 31.03 |
| **DoD + Liq** | | | | | | | | |
| **EWP** | 58.22 (9.61/1y) | 9.88 | **13.64** | 0.77 | 0.83 | 11.95 | 21.04 | **29.59** |
| **VWP** | 64.42 (10.46/1y) | 10.64 | 13.69 | 0.82 | 0.82 | 16.02 | **20.78** | **29.59** |
| **Min Mkt Cap DoD + Liq** | | | | | | | | |
| **EWP** | *16.93 (3.18/1y)* | *4.4* | *16.4* | *0.3* | 0.87 | *-18.4* | *26.67* | *37.76* |
| **VWP** | 20.55 (3.81/1y) | 4.95 | 16.13 | 0.34 | 0.87 | -15.45 | 26.11 | 36.92 |
| **Median Mkt Cap DoD + Liq** | | | | | | | | |
| **EWP** | 118.58 (16.93/1y) | 16.34 | 14.73 | 1.15 | *0.9* | 41.49 | 22.29 | 33.15 |
| **VWP** | 123.14 (17.41/1y) | 16.74 | 14.73 | 1.18 | *0.9* | 43.5 | 22.16 | 33.07 |

Table 6.7: Total results of the DoD with each modifications, on the EWP and VWP.

### 6.2.2 Magic Formula Improvement with Fundamentals and Reverse Momentum: Flowy Formula

**Motivation.** Davydov et al. (2016) decided to develop a study to compare the MF with other traditional value investment strategies in the Finnish market. Their sample consists of public businesses available for consultation in the Finnish Stock Exchange, from 1991 to 2013, where index values and stock prices come from NASDAQ OMX and financial variables from the Thomson Reuters Data stream database. In addition to put the MF to the test in the Finnish universe, they propose an augmented strategy with cash flow-to-price (CF/P) as an extra factor, which was inspired on earlier studies' suggestions for higher returns (see e.g., Lakonishok et al. (1994)). For this, CF is the sum of non-cash charges or credits (including depreciation and amortization items), net income and income statement deferred taxes. In the same way we'd usually rank the firms according to earnings yield and return on capital, we add a score by ranking according to CF/P, whereas the company with the highest CF/P gets a score of 1. In this sense, the perfect score remains at 3, instead of 2. The results showed that both strategies beat the market, since the MF (MF-CF) strategy produced an average annual return of 19.3% (20.2%), while the average annual return for the OMXH CAP GI was 13.6%. The Sharpe ratios were similar (0.641 and 0.684, respectively) and higher than the market's (0.380). To ensure impartiality, Davydov et al. (2016) decide to compare the augmented MF with traditional valuation ratios, book-to-price ratio (B/P) and CF/P, combined with return on capital, in the same technique as the original MF works. Once more, all of these strategies beat the market, especially CF/P with the highest abnormal return and best Sharpe ratio (Davydov et al., 2016). This comes to show that not only the MF proved to be a successful strategy in the Finnish market, but it received improvement with the addition of the factor cash flow-to-price.

Another paper focused on improving the MF for all size groups and regions was written by Blackburn and Cakici (2017). Their universe consisted on various countries from North America, Europe and Asia from January 1991 to December 2016. They chose to change the two fundamental factors, to be more directed towards gross profits selection. Instead of the EBIT in the computation of enterprise value, they use gross profits, and they change return on capital to gross profits divided by tangible capital (the sum of net working capital and fixed assets). They believed this two adaptations would refine the MF in a simple way, stating that measures on profitability such as EBIT are "noisy due to accounting items subtracted from earnings that may not be directly related to expenses incurred to generate revenues". Profitability measures such as gross profits, on another hand, are less noisy in terms of true and straightforward economic profitability. In their methodology, they choose the top quintile to buy and hold, with a monthly rebalance. They also experiment with the bottom quintile to see whether their factor implementation worked in their favour. Overall, they state their improved version of the MF did in fact outperform the MF in their scenario.

In an attempt of elevate a value investing strategy with a technical factor, Asness (1997) contributed by claimed that both value and momentum strategies are effective, but in their own way. While value strategies fail in firms with strong momentum, momentum strategies work better on expensive firms. These two methods of investing are negatively correlated, in the sense that pursuing a value strategy ensures buying firms with poor momentum, to some extent, and vice-versa.

These studies and papers lead us to verify the improvements on the MF and to attempt to use the supposedly inverse relationship between value and momentum strategy as an advantage.

**Methodology.** In this strategy, we use the cash flow-to-price ratio (CF/P), and, to stay close to the baseline strategies, the gross profit factor inspired from Blackburn and Cakici (2017) was taken from Piotroski (2000), being the gross margin ratio (GMR), and, finally, the relative strength (RS) from WL as the momentum technical factor.

The final strategy is simply the MF with two more fundamental factors, the CF/P, GMR, and the RS (also from the previous six months), which were added up to the baseline factors as the normal methodology of the MF, by retracting companies that belong in financial and utilities sectors. The prior universe is also the same as in the original MF. The fundamental factors were ranked in ascending order as the baseline factors and the technical factor was attached in a descending order with consideration of the past 6-month prices. This descending order is to test if using the momentum factor "backwards" would indeed improve the value strategy, although Asness (1997) did not suggest this directly. Since this was an attempt of improving a value based strategy, this investment was made yearly. Let us name this strategy Flowy Formula (FF).

**Results.** This subsection is dedicated to exhibiting and dissecting the results obtained by Qrumble when applying the Flowy Formula strategy in the European market during the period from 2015 to 2019.

When observing the Table 6.8, the results are disperse. The VWP achieved the highest ROI, Sharpe and beta, the EWP obtained the lowest standard deviation and TVaR, the MVP had the lowest mean, Sharpe, alpha and VaR and the MKTP received the lowest ROI and beta, and highest mean, standard deviation, alpha, VaR and TVaR. It is evident that the MVP and MKTP didn't meet their purpose, as they had low and/or very risky outcomes.

| Total | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 71.03 (11.33/1y) | 11.5 | **14.34** | 0.84 | 0.95 | 14.52 | 23.19 | **33.3** |
| **VWP** | **82.78 (12.82/1y)** | 12.86 | 14.8 | **0.91** | *0.96* | 20.85 | 23.67 | 34.15 |
| **MVP** | 34.12 (6.05/1y) | *6.87* | 15.05 | *0.5* | 0.73 | *1.0* | **22.0** | 35.16 |
| **MKTP** | *-1334.85 (-265.32/1y)* | **765.15** | *1305.85* | 0.59 | **0.66** | **3892.33** | *749.99* | *1763.88* |

Table 6.8: Total results on the 5-year investment based on Flowy Formula strategy.

As we can observe through the graph in Figure 6.7, only the simple holdings were able to outperform the market in the end and throughout of the five years of investment. The MKTP only accomplished this between March 2017 and, surprisingly, January 2019, when one could expect that the downfall would start in 2018. As anticipated by Table 6.8, the MVP was permanently below the benchmark.

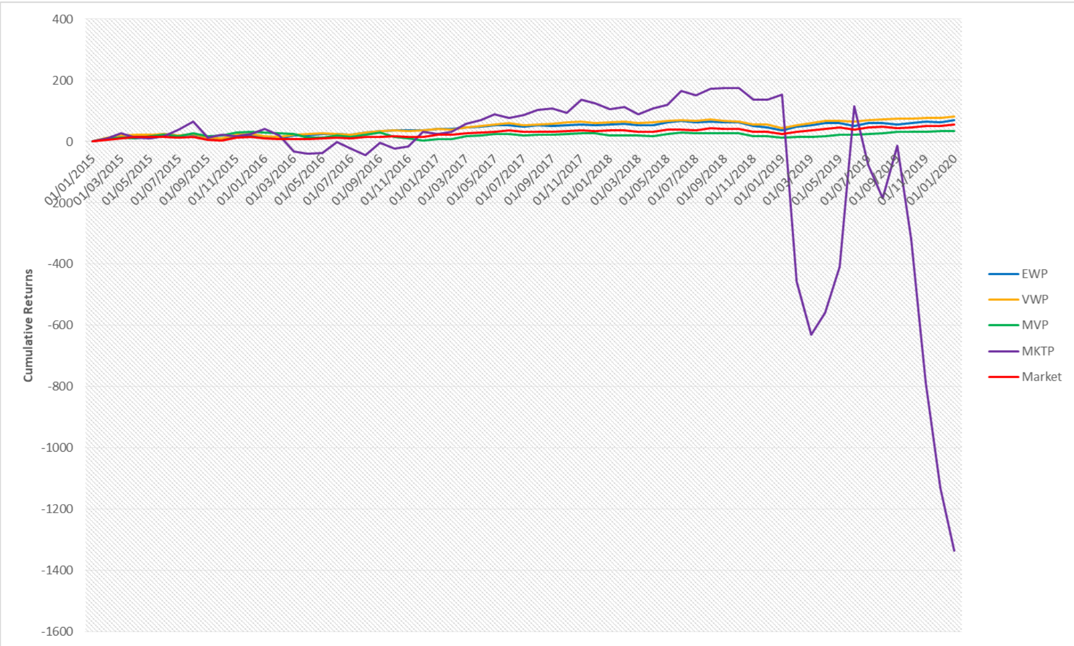


Figure 6.7: Cumulative returns evolution of the Flowy Formula strategy.

To examine the progression of the strategy over the course of five years of investment, we can observe on Table II.6 in Annex II, that the VWP didn't have the best ROI up until 2019, but accomplished best Sharpe three times, surpassing 2 in that year. As for the lowest standard deviation, the MVP achieved it only in the first year, being the EWP the major holder of this, as seen in the "Total" in Table 6.8. On another note, the MKTP has always had the highest mean, but there were times where the ROI didn't live up to this, both in 2016 and 2019. In regard of possible trends, the EWP and VWP follow similar patterns, more specifically, they grow in profit metrics in 2016 and 2019 and decrease in 2017 and 2018, and only increase standard deviation in 2018. Unusually, their VaR declines in 2016 but their TVaR doesn't do the same. The MVP and MKTP were predominantly moving in the opposite direction in all years but 2018, although the MKTP's standard deviation increased.

Within this experiment, a variety of assessments were performed to confirm the advantages of integrating both the CF/P factor and the gross profit factor, and to elucidate the ramifications of introducing a technical factor. These results can be seen on Table 6.9. In general, the MF gained an advantage with the addition of the fundamental factors mentioned above. At a first glance at the Table 6.9, GMR seems to be the factor that contributed more to this benefit, because of the increase of Sharpe and alpha values and slightly decrease of beta, VaR and TVaR. Thus, the MF + GMR strategy appears to be the best version of MF out of the four here presented. The technical factor was included on the MF and the MF + GMR to see if it had an impact on the baseline strategy and improved strategy, and it leaves ambiguous results, because it only improved the MF's EWP. We can clearly see that RS led to better results in Sharpe and alpha when added to the MF + GMR + CF/P. In the end, one can be torn between the MF + GMR and the FF, both in the VWP, for having such similar results.

Whilst comparing the results of the MF with the FF, we can say from Table 6.9, that than the additions onto the MF lead to greater ROIs and Sharpes on the simple portfolios. As for the risk measures, the MF performed slightly better but it doesn't seem to be an advantage for being such a small enhancement. As mentioned previously, the MKTP was able to shine in the MF, but fell through in the FF. Nonetheless, without considering the MKTP, the most secure holdings would the simple ones of the FF and maybe the VWP of the MF, since it outperforms the market and had an equal Sharpe to the EWP of the FF. When contrasting these results with the original WL, we can state with confidence that the addition of the fundamental factors had a very positive impact overall, both in profit and risk metrics.

| **MF** | **ROI % (annual)** | **Mean %** | **St Dev %** | **Sharpe** | **Beta** | **Alpha %** | **VaR/1y %** | **TVaR/1y %** |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 44.77 (7.68/1y) | 8.22 | 14.17 | 0.62 | 0.93 | *-1.24* | 22.54 | 33.39 |
| **VWP** | 69.22 (11.09/1y) | 11.26 | 14.10 | 0.84 | 0.89 | 16.01 | 22.36 | 31.73 |
| **MF + GMR** | | | | | | | | |
| **EWP** | 60.33 (9.9/1y) | 10.26 | 14.47 | 0.75 | 0.94 | 8.52 | 22.7 | 33.96 |
| **VWP** | **85.92 (13.21/1y)** | **13.07** | 13.94 | **0.98** | 0.88 | **25.93** | 22.32 | **31.51** |
| **MF + CF/P** | | | | | | | | |
| **EWP** | 50.3 (8.49/1y) | 9.15 | 15.49 | 0.63 | 0.99 | 0.26 | **24.74** | 35.47 |
| **VWP** | 50.03 (8.45/1y) | 9.13 | 15.6 | 0.62 | *1.01* | -0.81 | 25.12 | 36.02 |
| **MF + GMR + CF/P** | | | | | | | | |
| **EWP** | 61.05 (10.0/1y) | 10.44 | 15.07 | 0.73 | 0.98 | 7.73 | 23.69 | 35.16 |
| **VWP** | 64.55 (10.47/1y) | 10.77 | 14.53 | 0.78 | 0.95 | 10.76 | 23.21 | 33.81 |
| **WL** | | | | | | | | |
| **EWP** | 12.16 (2.32/1y) | 3.4 | 17.0 | 0.24 | **0.06** | 15.03 | *26.68* | 38.02 |
| **VWP** | *-20.06 (-2.89/1y)* | *-1.56* | *21.79* | *-0.04* | -0.31 | 7.16 | 31.33 | *51.73* |
| **MF - RS** | | | | | | | | |
| **EWP** | 43.65 (7.51/1y) | 8.07 | 14.19 | 0.61 | 0.9 | -0.94 | 24.58 | 33.45 |
| **VWP** | 60.11 (9.87/1y) | 10.17 | 14.08 | 0.77 | 0.88 | 10.86 | 23.5 | 32.74 |
| **MF + GMR - RS** | | | | | | | | |
| **EWP** | 53.78 (8.99/1y) | 9.36 | 13.9 | 0.72 | 0.91 | 5.42 | 22.86 | 32.66 |
| **VWP** | 52.63 (8.82/1y) | 9.21 | **13.86** | 0.71 | 0.86 | 6.88 | **22.24** | 32.22 |
| **MF + GMR + CF/P - RS** | | | | | | | | |
| **EWP** | 71.03 (11.33/1y) | 11.5 | 14.34 | 0.84 | 0.95 | 14.52 | 23.19 | 33.3 |
| **VWP** | 82.78 (12.82/1y) | 12.86 | 14.8 | 0.91 | 0.96 | 20.85 | 23.67 | 34.15 |

Table 6.9: Total results of the MF and WL with each modifications, on the EWP and VWP.

### 6.2.3 Magical Bambu

**Motivation.** The idea behind this strategy was to add other fundamental factors directly focused on assets to the MF alongside with the technical factor of WL in its normal ranking order. The concept also relies in choosing fewer companies, twenty instead of thirty to be exact. Firstly, we thought of changing the return on capital factor from the MF, to annual return on asset difference factor (ΔROA) from Piotroski (2000). Then, in another inspiration from Piotroski (2000), we added the annual difference in asset turnover (ΔTURN). These two fundamental factors from the F_score are supposed to be better in terms of defining valuable assets whilst using their variation in value between two consecutive years. Following that, as the dividend yield (Yield) factor is always well supported in academic works (see Fama and French (1992), Singh and Walia (2022)) and also seemed to work in the first case study, Liquid Median DoD, it proved to be interesting enough to be taken into consideration. In the end, we included the rising RS factor as the pioneering WL uses for winner stocks, in an attempt of combining value strategy with a rising technical factor from momentum strategies.

**Methodology.** The procedure of this new investment strategy idea is homologous to the last one in terms of combining the factors. To be more precise, all of the factors mentioned above were added in the ranking, so they have equal influence. Similarly to the FF, the initial universe is equal to the original MF. To summarise, what we modified in this strategy compared to the previous one are most of the fundamental factors – ΔROA instead of ROC, ΔTURN and Yield –, the size of the final choice, being twenty now, and the way the RS is ranked, in an ascending order as in WL. Let's refer to this strategy as Magical Bambu (MB).

**Results.** As we can observe on Table 6.10, the MKTP achieved the greatest ROI, mean and alpha, but the portfolio that accomplished the highest Sharpe was actually the VWP, which resulted on the second largest ROI. In terms of standard deviation, the MVP fulfills its goal by having the lowest one, and also smallest beta, VaR and TVaR. There seems to be a very limited correlation between beta and returns because the MVP obtained the smallest returns but the EWP had a high ROI (compared to other ROIs in other experiments) and achieved the highest beta. On another hand, per usual, the MKTP reached the highest standard deviation and, consequently, VaR and TVaR, but these results don't differ much from the other portfolios, when remembering the huge disparity on risk metrics on the baseline strategies, for example. This brings a sense of security, because not only we attained extraordinary profit results, but we were spared from enduring significantly increased risk levels, even at the portfolio already known for compromising the final outcomes.

| Total | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 98.48 (14.69/1y) | 14.56 | 15.42 | 0.98 | *0.94* | 30.47 | 23.86 | 35.47 |
| **VWP** | 128.27 (17.95/1y) | 17.28 | 15.32 | **1.17** | 0.89 | 46.86 | 24.06 | 33.53 |
| **MVP** | *69.95 (11.19/1y)* | *11.32* | **13.97** | *0.85* | **0.71** | *24.95* | **22.77** | **31.61** |
| **MKTP** | **218.9 (26.1/1y)** | **26.62** | *28.34* | 0.96 | 0.78 | **99.88** | *40.15* | *61.92* |

Table 6.10: Total results on the 5-year investment based on Magical Bambu strategy.

Put simply, the graph in Figure 6.8 clearly displays how remarkable and reliable the Magical Bambu turned out to be. Alongside this, every single holding outperformed the benchmark consistently and even managed to survive the 2018 market crash effortlessly.

The evident winner in cumulative returns was the MKTP with its sudden rise in September 2019, but the winner within the simple portfolios remains the VWP.

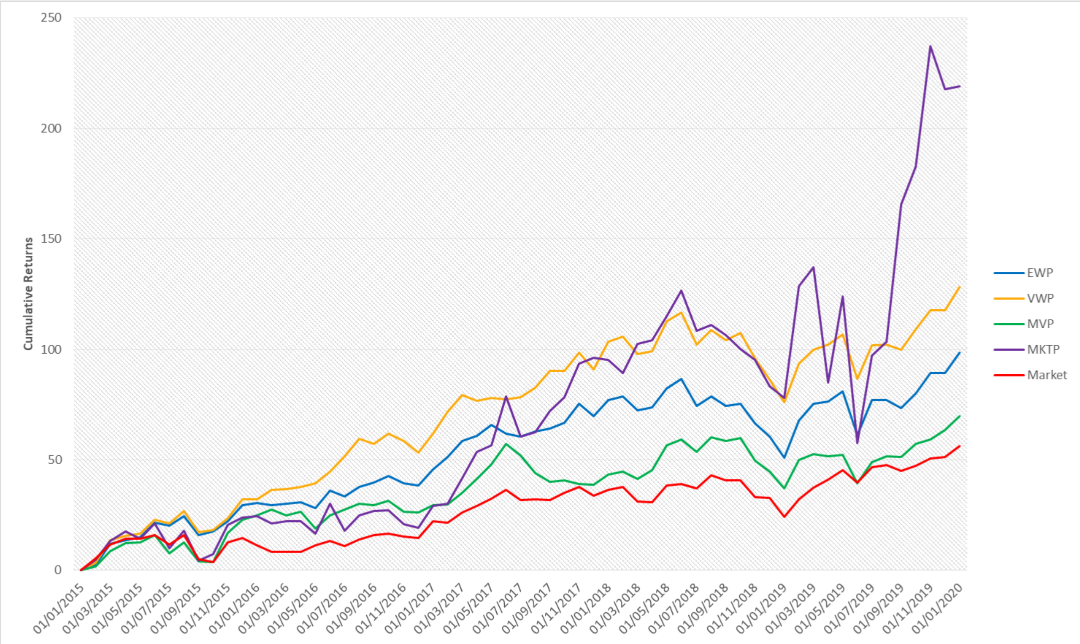


Figure 6.8: Cumulative returns evolution of the Magical Bambu strategy.

When analising the results through the time period on Table II.7 in the Annex II, it is interesting to see that the VWP always had a Sharpe superior to 1, except in the year of 2018. This is an unique feature that exclusively occurred in this investment strategy. Another thing special about these results is that there is also a recurring trend in profit metrics, but in this case there aren't exceptions, i.e. every portfolio follows the same direction. This leads to the perception that the weighting scheme didn't have a drastic effect, specially since any weight formation lead to outperformance of the market. Besides this, we can reiterate the same points that were previously mentioned on the other investment strategies. The MVP is the portfolio that has achieved the lowest standard deviation, VaR and TVaR the most times, and, interestingly enough, had the highest values in all profit measures in 2018. In fact, both the VWP and MKTP achieved the largest profit metrics two times throughout the five years.

The Table 6.11 below provides a sense of the impact of the additions and modifications of the original MF choosing 20 assets (MF20), and a final comparison with the WL, DoD and F_score results, all in the simple portfolios. As in the prior created portfolios, the results of each alteration and addition display how the investment strategy came to be and the effect of each factor. To be concise, the ΔROA had a positive impact in the MF20 in both portfolios and the addition of the ΔTURN had better results than the first modification, in the EWP and slightly worse on the VWP, both in profit and risk measures. When inserting the Yield in this experiment, both portfolios suffered a bit in the ROI, but due to the better risk measures, had a slighly better Sharpe ratio. Since we weren't exactly sure if the Yield addition was a good choice, we experimented the introduction of the technical factor RS in the MF20 w/ΔROA + ΔTURN, and comparing this investment strategy with the MB, we can say that the Yield had a good impact in the last strategy, since the ROI, Sharpe values were much higher, and there was little to know difference between all of their risk measures. Finally, when contrasting the MB with all baseline strategies, since it possesses factors from each one, we can state that all original strategies overall benefited from this fusion, from ROI, annualized and Sharpe, to VaR and TVaR.

When comparing the MB with the baseline strategies with the help from Table 6.11, our new investment strategy lead to greater returns and performances overall. Not only all of the profit measures improved on every holding, but the increase in risk did not exhibit a substantial disparity, when comparing to DoD and the MF, and it was even diminished, when compared to WL and the F_score (specially on the MKTP). The only portfolio that decreased in ROI was the MVP, being larger in the F_score, but its Sharpe was much bigger in the MB.

| **MF20** | **ROI % (annual)** | **Mean %** | **St Dev %** | **Sharpe** | **Beta** | **Alpha %** | **VaR/1y %** | **TVaR/1y %** |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 42.59 (7.35/1y) | 7.95 | 14.34 | 0.6 | 0.89 | -1.08 | 22.77 | 34.1 |
| **VWP** | 71.93 (11.45/1y) | 11.6 | 14.33 | 0.85 | 0.85 | 19.8 | 22.78 | 32.1 |
| **MF20 w/ΔROA** | | | | | | | | |
| **EWP** | 70.99 (11.33/1y) | 11.84 | 16.54 | 0.75 | 1.02 | 12.77 | 25.84 | 38.03 |
| **VWP** | 100.48 (14.93/1y) | 14.73 | 15.2 | 1.01 | 0.94 | 31.38 | 24.31 | 34.22 |
| **MF20 w/ΔROA + ΔTURN** | | | | | | | | |
| **EWP** | 80.8 (12.57/1y) | 12.79 | 15.69 | 0.85 | 0.98 | 19.47 | 24.51 | 35.6 |
| **VWP** | 91.01 (13.82/1y) | 13.85 | 15.63 | 0.92 | 0.94 | 26.92 | 25.59 | 34.75 |
| **MF20 w/ΔROA + ΔTURN + Yield** | | | | | | | | |
| **EWP** | 73.3 (11.62/1y) | 11.82 | 14.78 | 0.84 | 0.94 | 16.49 | 22.89 | 34.4 |
| **VWP** | 82.43 (12.78/1y) | 12.74 | 14.26 | 0.94 | 0.88 | 24.29 | 22.83 | 32.61 |
| **WL** | | | | | | | | |
| **EWP** | 12.16 (2.32/1y) | 3.4 | 17.0 | 0.24 | **0.06** | 15.03 | 26.68 | 38.02 |
| **VWP** | *-20.06 (-2.89/1y)* | *-1.56* | *21.79* | *-0.04* | -0.31 | 7.16 | 31.33 | 51.73 |
| **MF20 w/ΔROA + ΔTURN + RS** | | | | | | | | |
| **EWP** | 70.18 (11.22/1y) | 11.77 | 16.73 | 0.74 | 1.0 | 13.58 | 26.62 | 38.34 |
| **VWP** | 77.1 (12.11/1y) | 12.5 | 16.44 | 0.8 | 0.95 | 19.35 | 27.28 | 36.74 |
| **DoD** | | | | | | | | |
| **EWP** | 43.2 (7.45/1y) | 7.97 | **13.93** | 0.62 | 0.88 | -0.56 | 22.35 | **30.58** |
| **VWP** | 44.51 (7.64/1y) | 8.17 | 14.03 | 0.62 | 0.89 | 0.25 | **21.60** | 30.83 |
| **F_score** | | | | | | | | |
| **EWP** | 73.44 (11.64/1y) | 12.58 | 19.19 | 0.69 | 0.94 | 20.31 | *31.71* | 41.29 |
| **VWP** | 72.96 (11.58/1y) | 12.6 | 19.57 | 0.67 | 1.11 | 12.26 | 30.99 | *43.31* |
| **MB** | | | | | | | | |
| **EWP** | 98.48 (14.69/1y) | 14.56 | 15.42 | 0.98 | 0.94 | 30.47 | 23.86 | 35.47 |
| **VWP** | **128.27 (17.95/1y)** | **17.28** | 15.32 | **1.17** | 0.89 | **46.86** | 24.06 | 33.53 |

Table 6.11: Total results of the MF and WL with additions, on the EWP and VWP, and comparison with the DoD and F_score.

## 6.3 Discussion

### 6.3.1 Portfolio Behaviour

After analising each and every investment strategy, there were some key points important to note out about the general performance of each strategy by metric.

At first, ROI achieved higher values mainly in the MKTP by four times and the VWP by three times. The standard deviation, and consequently, VaR and TVaR, were mostly lower on the MVP (in five times), and they were the highest in the MKTP, in every case. We also shouldn't disregard the minimum ROI, but it will be addressed shortly. The best Sharpe was predominately from the VWP (in five times) and the worst one was found at the MKTP three times, joined with a negative ROI, the EWP and MVP, each two times. We could say that the MKTP experienced an excess of risk exposure, resulting in unfavorable outcomes. It's worth mentioning that MVP from the Magical Bambu strategy and MKTP from the F_score were the only holdings with the worst Sharpe that had a ROI that surpassed the benchmark.

Regarding a different matter, let us see if the MVP was more efficient in terms of a higher Sharpe in times where the VWP didn't succeed in the maximum ROI category. This is interesting to point out, because we could disregard the MKTP for its enormous amount of risk and still want to comprehend which holding was more efficient in those cases. In the WL, it is undeniable that the MVP was more efficient, since it obtained a higher ROI and Sharpe, and low standard deviation. In the F_score method, the MKTP achieved highest ROI, but the MVP was still the holding to receive best Sharpe value.

As for betas, the portfolio to achieve lowest beta more times was the MKTP but there isn't a clear correlation to ROI. To be exact, the MKTP had lowest ROI and absolute lowest beta in four strategies, the DoD and the three created mixture strategies. The MKTP also had the bottom ROI and top beta in the WL. Speaking of highest betas, the values were more scattered, having the VWP and MKTP obtained it three times and the EWP two times.

### 6.3.2 Investment Strategy Comparison

Comparing investment strategies can be challenging due to the vast array of metrics and their respective meanings. However, the importance of each metric depends on investor preference and there is no absolute right or wrong. Risk-averse investors may prefer portfolios like the MVP, with DoD providing the lowest risk, although the MVPs in other investment strategies provided close results in standard deviation, VaR and TVaR. Investors willing to take higher risks for higher returns could go for the MKTP in the F_Score or MF, while those seeking higher Sharpe ratios may prefer VWP, particularly in Median DoD, Liquid Median DoD and Magical Bambu. To compare Sharpe ratios across all strategies, the values achieved by portfolios within each investment strategy are displayed in Table 6.12 below. It's worth noting that the most successful investment strategies in terms of Sharpe ratio were the ones we created, not those derived from expert studies. Additionally, while the Magical Bambu didn't attain the highest Sharpe ratio, it consistently maintained high ratios across all portfolios, unlike LMDoD and MDoD, where one or two portfolios fell short in this metric.

| **Sharpe** | **DoD** | **WL** | **F_score** | **MF** | **LMDoD** | **MDoD** | **FF** | **MB** |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 0.62 | 0.24 | 0.69 | 0.62 | 1.15 | 1.28 | 0.84 | 0.98 |
| **VWP** | 0.62 | -0.03 | 0.67 | 0.84 | **1.18** | **1.3** | 0.91 | **1.17** |
| **MVP** | 0.48 | 0.63 | 0.76 | 0.67 | 0.47 | 0.7 | 0.5 | 0.85 |
| **MKTP** | 0.07 | -0.13 | 0.55 | 0.78 | 0.26 | 0.28 | 0.59 | 0.96 |

Table 6.12: Sharpe ratio comparison in every investment strategy.

Furthermore, during evaluation, certain investors might discard other investment strategies based on negative ROIs, as seen in DoD and WL, where neither portfolio outperformed the market, or in the case of LMDoD and FF, which demonstrated interesting outcomes in the simple portfolios. Consequently, these investors might lean toward feeling more secure with other strategies. Referring to the simple portfolios, investors might also favor EWP and VWP due to their familiarity, considering strategies like Magical Bambu, F_Score, or even MDoD, as each portfolio outperformed the market. Alternatively, they may consider LMDoD and FF, where solely the simple portfolios achieved this. These choices offer interesting results in ROI and higher Sharpe ratios compared to their counterparts in the same portfolios.

Overall, following this analysis, it's notable that the Magical Bambu and F_score emerge as particularly compelling investment strategies within this criteria and dataset.

### 6.3.3 Investment Strategies of Distinction

Throughout this whole study, there were two investment strategies that caught our eye.

At first, we have the DoD with a median market capital accomplished the highest Sharpe and ROI in the VWP, followed by a little increase in risk overall. Not only the new selection on the market capital in the original DoD had a huge positive impact, but this specific holding provided a very interesting result. Unfortunately, this investment strategy didn't attain astounding results on every holding that was applied to, which leaves some uncertainty (see Table II.8 in Annex II). For example, although the MVP has a better Sharpe value in this modified DoD, it barely outperformed the market in the end. Moreover, the MKTP received an enormous ROI, but didn't succeed at the Sharpe value as the other holdings did.

Secondly, the very last investment strategy, Magical Bambu, substantiated as a compelling methodology for superior and safe outcomes. It was also the VWP that showcased the most appealing results, yet the other portfolios also got an opportunity to shine, as they all exceeded the benchmark and the lowest Sharpe value was of 0.85 by the MVP. As mentioned previously on its analysis, the increases in risk weren't as elevated as one would expect with these ROIs and, most importantly, no portfolio dealt with complete failure. This last aspect is notable, in the sense that no other investment strategy accomplished this, the closest being the MF, which got median to high Sharpe values but its EWP and MVP didn't overachieve the market.

### 6.3.4 Magical Bambu

On account of to the last paragraph, we conducted an analysis to comprehend what went behind this success, particularly on the VWP. This study was directed towards the three or four most influential stocks of each year, and their price variation, between the last and the first day of investment. It should be noted that these assets do not come in any particular order, nor they are the only assets bought each year, since this investment strategy selected twenty assets yearly.

As expected, the Table 6.13 confirms the general idea that the most dominant equities were granted of impressive and overall very positive price fluctuation. There were even some repeatedly chosen assets, such as BAE Systems (BA.L), Anglo American (AAL.L) and Equinor ASA (EQNR.OL).

| **Companies in 2015** | **Weight %** | **Price Variation %** |
|---|---|---|
| **PNDORA.CO** | 9.4 | 73.69 |
| **ASSA-B.ST** | 12 | 35.12 |
| **CAP.PA** | 10 | 45.2 |
| **BA.L** | 14.2 | 12.37 |
| **Companies in 2016** | | |
| **GSK.L** | 39.5 | 20.63 |
| **BA.L** | 9.3 | 24.81 |
| **ADS.DE** | 9.3 | 73.98 |
| **Companies in 2017** | | |
| **BA.L** | 11.7 | 0.38 |
| **RIO.L** | 23.6 | 32.34 |
| **AAL.L** | 8.8 | 38.43 |
| **Companies in 2018** | | |
| **EQNR.OL** | 10.7 | 7.39 |
| **AAL.L** | 9.1 | 15.24 |
| **CFR.SW** | 21.7 | -27.76 |
| **Companies in 2019** | | |
| **EQNR.OL** | 11.4 | 0.17 |
| **ITX.MC** | 13.8 | 45.02 |
| **ENI.MI** | 19.4 | 6.54 |

Table 6.13: Price variations on the impactful assets chosen each year by the Magical Bambu and their corresponding weight on the VWP.

# Chapter 7

# Conclusion

This study focused on experimenting the referenced baseline strategies in Qrumble framework with more metrics than usual, applying them in other two important theoretically efficient portfolios and creating new multi-factor investment strategies. The environment considered for these tests and ideas was the biggest European stock market, within the period from 2015 to 2019. The implementation of more measures provided a broader perception of each portfolio for evaluation. The theoretically efficient portfolios displayed interesting performances in all strategies, even perpetuating better results in some few cases, depending on investors preferences.

Firstly, we confirm that Qrumble is a powerful toolbox, capable of joining a range of factors, in various sorts of rankings and screenings. It is also effective in rapidly repeating multiple investment test-cases as often as required and displaying the results in a clear and visible format. Currently, Qrumble is undergoing through some improvements inspired within this work. We have also noticed that Qrumble possesses an obstacle when it comes to calculating certain daily returns, as seen on the Buying Winners and Selling Losers investment strategy. This barrier originated by a numerical issue in the denominator of the daily returns, when the portfolio value is almost null, and the portfolio return approaches -100%, creates impactful outliers that can change our perception in the observation of mean and standard deviation of returns. Another ocurrence of this was the drastic decline in cumulative returns in the F_score, which highlights the necessity for comprehensive analysis in future work when conducting simulations of investment strategies.

As for the contributions in Qrumble regarding Portfolio Theory, there are some key considerations to highlight. Although ROI and Sharpe ratio are crucial to portfolio evaluation, the addition of beta, alpha, VaR and TVaR allowed for a broader vision within the comparison of performances, specially the metrics of possible losses. Particularly, VaR and TVaR are modern tools that offered us a more specific measure for potential losses.

Although beta and alpha served for understanding what was behind each portfolio better, both were inconclusive in determining the wellness of the portfolios. Just because the measure is absolutely higher, it doesn't necessarily translate into good or bad results, since it mostly depends on the investor and the state of the market, and that requires better forecasts of the stock market.

Regarding different weight schemes, the value-weighted portfolio was the portfolio that achieved greater findings normally in ROI and Sharpe with little to no rising on the risk metrics, when compared to the equal-weighted portfolio or minimum variance portfolio. The value-weighted portfolio can also work as an index, taking into account that the choice is based on fundamental indicators and betting on larger companies is good for consistency of results. The market portfolio could also be very appealing, depending on the investment strategy, but its usual elevated amount of risk associated with those exponential returns could have a negative impact in the end, potentially leading to negative cumulative returns that are challenging to recover from, let alone surpass the market in the long run. The investment strategy that propels the usage of the market portfolio the most would be the Magical Bambu, where it got the largest Sharpe ratio in and lowest quantity of risk and possible yearly losses, compared to all market portfolio experiences. The F_score and Magic Formula also exhibited exorbitant returns, alongside with huge risk. Therefore, this portfolio would be the most desirable by not so risk-averse investors. In reference to the minimum variance portfolio, it mainly met its intended function as the portfolio with the least amount of risk, except for the Dogs of the Dow and its alterations, and the Flowy Formula.

About the performance of the investment strategies, and after the comparison of all investment strategies in **6.3.3** for each possible investor preference, each strategy revealed interesting aspects to emphasize. Regarding the Dogs of the Dow and the combinations envolving it in **6.2.1**, the appliance of the Dogs of the Dow with a median market capital seemed to be the best fully fundamental version of this investment strategy, providing better results than the original, specially in the simple portfolios. This is noteworthy because we didn't find suggestions of using median firms in the midst of small-firm/ big-firm discussion in research. It would be interesting to see more studies done on the median market capital tested in an already big market, such as the European one. Another aspect is that the liquidity factor appeared to be a strong factor in the Dogs of the Dow and could even flourish with other scenarios, environments and combinations in future work. About the Buying Winners and Selling Losers, the minimum variance portfolio seemed to have understood better which shares to buy and sell than the original strategy , since it had a Sharpe ratio greater than 1 three times, was the closest to the benchmark at the end of 2019, and the portfolio with the lowest risk, VaR and TVaR in all five years. As for the F_score, it was interesting to see the simple portfolios having close results to the minimum variance portfolio, and tremendous cumulative returns in the market portfolio. Concerning the Magic Formula, it was the strategy that seemed to pervail between the baseline strategies, in terms of having the largest Sharpe ratio overall and still low VaR and TVaR measures. As for one of the created investment strategy that had the Magic Formula as the main base, the reverse RS factor did in fact enhance the results of MF + GMR + CF/P and was much better than the ones from Buying Winners and Selling Losers. The gross margin ratio gives the impression of being the fundamental factor that had a bigger positive impact on the Flowy Formula, which could be studied in future work.

In all the strategies in which there appears to be success, the results of the comparative studies were almost always better. It is plausible that the year 2018 and its turmoils were what kept us from achieving better results. To bridge this gap, one potential approach is to carry on the successful investment strategies for more years, since our time period was less than half that of the comparative studies.

About the size effect, the fact that the value-weighted portfolios provided the better results and performances, and the way the market capital reversed on Dogs of the Dow worsened the outcomes suggest that the size effect was not observed within our results. On the other hand, the Buying Winners and Selling Losers counterbalanced this, when the equal-weighted portfolio had better results than the value-weighted portfolio, even though they could both be considered mediocre. This event is one that could agree with the size effect. This may have happened because big winners can only grow up to a certain point and can't rise any further, and/or the big losers had the strength to rise quickly in six months. Let us not forget that the European stock market applied within these experiments is composed of the 600 biggest companies in Europe, so it's a sizable asset versus an even larger asset. On another hand, the F_score also had higher returns with less risk in the equal-weighted portfolio compared to the value-weighted portfolio, but the differences were so minimal that it remains unclear if the size effect is present in this case.

Finally, in regard to the very last investment strategy, the Magical Bambu, it can be considered the most eye-catching strategy, because it provided very high profits without needing much more risk to do so, and all the portfolios tested beat the market. If we were to reduce our concerns about the risk premium measured by Sharpe, the market portfolio could be even better than the value-weighted portfolio (winner of best Sharpe), because the market portfolio obtained a higher ROI and annualized and its VaR and TVaR weren't very different from those of the other portfolios. Another aspect that brings security to this investment strategy was the way all portfolios followed the same trend and were all very successful by surpassing the benchmark. Any selection of weights went well with the assets chosen by this method. The usage of fundamental factors that measure the yearly differences in certain aspects of each business could be a more impartial and fair approach for comparison and selection, due to the variability among companies. After all, the usage of both fundamental and technical analysis can generate impressive outcomes.

Besides of the suggestions left above, we also propose future work about blending momentum strategies with dividends or dividend yield factor (see Asness (1997)) and value strategies with other technical factors like volatility. Like most if not all research, the application of bootstraping and price simulation to perform better estimations and significant statistic tests would also be captivating.

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# Annex I

```
from contextlib import contextmanager
import logging
import qrumble as q
from qrumble.factors import *
import qrumble.universe

FUNDAMENTALS="data-stoxx600/FUNDAMENTALS.2015_2019.pickle"
OHLCV="data-stoxx600/stoxx600.jan2014_dec2019.pickle"
RF=-0.6

q.configureLog(logging.BASIC)
q.weights.configureLog(logging.INFO)

#Load sample dataframes
funda = q.load(FUNDAMENTALS)
ohlcv = q.load(OHLCV)
```

Listing I.1: Data implementation in Qrumble.

```
with testcase("Evaluate the performance of the strategy 'Dogs of the Dow'.",
            "See the strategy's overall performance by running it monthly in 2015--2019:"):
    results, df, df0 = q.qrumble("dogs_final:{DATE}/rank/10", "dogs_final:{DATE}/play/10/1y", "jan2015", "5y", periodicity='1m', rebalance = '1y',
                    fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05, fee = 0,
                    universe_list=q.universe.fetch,
                    universe=lambda f: f.Ranking(MktCap()(ascending), top= 30),
                    criteria=lambda f: f.Ranking(Yield()(ascending), top= 10 ),
                    weight_function=q.mktp_weighted,
                    dataframe="both")
```

```
    print(results)
```

Listing I.2: Qrumble's Testcase for the Dogs of the Dow strategy for five years in the MKTP.

```
with testcase("Evaluate the performance of the strategy 'Winners and Losers'."
    ,
            "See the strategy's overall performance by running it monthly in
    2015--2019:"):
    results, df, df0 = q.qrumble("wl:{DATE}/rank/10", "wl:{DATE}/play/10/1y",
    "jan2015", "5y", periodicity='1m', rebalance = '6m',
                    fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05,
                    universe_list=q.universe.fetch,
                    criteria=lambda f: f.Ranking('winners')(RS('6m')(ascending
    ),  top='10%')\
                                        .Ranking('losers')(RS('6m')(descending
    ), top='10%'),
                    strategy=('buy&hold', 'short'),
                    fee=0.0,
                    weight_function=q.equal_weighted,
                    dataframe="both")
    print(results)
```

Listing I.3: Qrumble's Testcase for the Winners and Losers strategy for five years in the EWP.

```
def universe(f):

    f.Ranking(BM()(ascending), top="20%")
    return f

def fscore(f):
    profitability = (ROA()>0).astype(int) + (OCF()>0).astype(int) + (ROA_diff
    ()>0).astype(int) + (AccrualRatio()<0).astype(int)
    leverage_liquidity = (LTDebt_to_Assets_diff()<0).astype(int) + (
    CurrentRatio_diff()>0).astype(int) + (ShareIssuance()<=0).astype(int)
    operating_efficiency = (OpMgn_diff()>0).astype(int) + (AssetTurnover_diff
    ()>0).astype(int)
    f.Ranking('9')(profitability + leverage_liquidity + operating_efficiency,
    score=9)
    f.Ranking('8')(profitability + leverage_liquidity + operating_efficiency,
    score=8)
    f.Joining('8', '9', into='high')
    f.Ranking('0')(profitability + leverage_liquidity + operating_efficiency,
    score=0)
    f.Ranking('1')(profitability + leverage_liquidity + operating_efficiency,
    score=1)
    f.Joining('0', '1', into='low')
    return f

with testcase("Evaluate the performance of the strategy 'Piotroski's F-Score'
    without financials and utilities.",
```

```
                "See the strategy's performance in 2015--2019:"):
    results, df, df0 = q.qrumble("f-score:{DATE}/rank/{L}", "f-score:{DATE}/
    play/1y",
                            "jan2015", "5y", rebalance="1y", periodicity="1d",
                            fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05,
                            universe_list=q.universe.fetch,
                            universe=universe,
                            criteria=fscore,
                            strategy=('buy&hold', 'short'),
                            fee=0.0,
                            weight_function=q.value_weighted,
                            dataframe="both")
    print(results)
```

Listing I.4: Definitions of the environment screening and F_score criteria and its testcase for five years in the VWP in Qrumble.

```
with testcase("Evaluate the performance of the strategy 'Magic Formula'.",
              "See the strategy's overall performance by running it monthly in
    2015--2019:"):
    results, df, df0 = q.qrumble("magic_formula:{DATE}/rank/10", "
    magic_formula:{DATE}/play/10/1y", "jan2015", "5y", periodicity='1m',
    rebalance = '1y',
                        fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05, fee =
    0,
                        universe_list=q.universe.fetch,
                        universe=lambda f: f.Screening(~Sector().isin(['banking',
    'insurance', 'real estate', 'financial', 'utilities', 'waste'])),
                        criteria=lambda f: f.Ranking(EarningsYield()(ascending) +
    ROC()(ascending), top=30),
                        weight_function=q.value_weighted,
                        dataframe="both")
    print(results)
```

Listing I.5: Qrumble's Testcase for the Magic Formula strategy for five years in the VWP.

```
with testcase("Evaluate the performance of the strategy 'Liquid Median Dogs of
     the Dow'.",
              "See the strategy's overall performance by running it monthly in
    2015--2019:"):
    results, df, df0 = q.qrumble("limedogs
    :{DATE}/rank/10", "limedogs:{DATE}/play/10/1y", "jan2015", "5y",
    periodicity='1m', rebalance = '1y',
                        fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05, fee =
    0,
                        universe_list=q.universe.fetch,
                        universe=lambda f.Ranking(MktCap()(descending), top= '50%'
     )\
                                         .Ranking(MktCap()(ascending), top= '20%'
    ),
```

```
                criteria=lambda f: f.Ranking(Yield()(ascending) + CurrentRatio_diff()(ascending), top= 10 ),
                weight_function=q.mktp_weighted,
                dataframe="both")
    print(results)
```

Listing I.6: Qrumble's Testcase for the Liquid Median Dogs of the Dow strategy for five years in the MKTP.

```
with testcase("Evaluate the performance of the strategy 'Flowy Formula'.",
            "See the strategy's overall performance by running it monthly in 2015--2019:"):
    results, df, df0 = q.qrumble("ff:{DATE}/rank/10", "ff:{DATE}/play/10/1y", "jan2015", "5y", periodicity='1m', rebalance = '1y',
                fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05, fee = 0,
                universe_list=q.universe.fetch,
                universe=lambda f: f.Screening(~Sector().isin(['banking', 'insurance', 'real estate', 'financial', 'utilities', 'waste'])),
                criteria=lambda f: f.Ranking(EarningsYield()(ascending)  + ROC()(ascending) + OCFP()(ascending) + OpMgn_diff()(ascending) + RS('6m')(descending), top=30),
                weight_function=q.mvp_weighted,
                dataframe="both")
    print(results)
```

Listing I.7: Qrumble's Testcase for the Flowy Formula strategy for five years in the MVP.

```
with testcase("Evaluate the performance of the strategy 'Magical Bambu'.",
            "See the strategy's overall performance by running it monthly in 2015--2019:"):
    results, df, df0 = q.qrumble("MB:{DATE}/rank/10", "MB:{DATE}/play/10/1y", "jan2019", "1y", periodicity='1m', rebalance = '1y',
                fundamentals=funda, ohlcv=ohlcv, Rf=RF, Alpha=0.05, fee = 0,
                 universe_list=q.universe.fetch,
                universe=lambda f: f.Screening(~Sector().isin(['banking', 'insurance', 'real estate', 'financial', 'utilities', 'waste'])),
                criteria=lambda f: f.Ranking(EarningsYield()(ascending) + ROA_diff()(ascending) + AssetTurnover_diff()(ascending) + Yield()(ascending)  + RS('6m')(ascending), top=20),
                strategy=('buy&hold'),
                weight_function=q.value_weighted,
                dataframe="both")
    print(results)
```

Listing I.8: Qrumble's Testcase for the Magical Bambu strategy for five years in the VWP.

```
            roi/6m   roi%   cum%  daily%
Date
2019-01-01  -87.26  +0.00  +0.00     NaN
```

```
2019-01-02      NaN  +0.00  +0.00   +0.00
2019-01-03      NaN  +4.86  +4.86   +4.86
2019-01-04      NaN -10.48 -10.48  -14.63
2019-01-07      NaN  -9.31  -9.31   +1.30
2019-01-08      NaN  -3.55  -3.55   +6.35
2019-01-09      NaN  -1.55  -1.55   +2.07
2019-01-10      NaN  -8.97  -8.97   -7.53
2019-01-11      NaN -10.94 -10.94   -2.16
2019-01-14      NaN -16.38 -16.38   -6.11
2019-01-15      NaN  -9.88  -9.88   +7.76
2019-01-16      NaN -15.87 -15.87   -6.65
2019-01-17      NaN -18.73 -18.73   -3.39
2019-01-18      NaN -26.64 -26.64   -9.73
2019-01-21      NaN -33.35 -33.35   -9.15
2019-01-22      NaN -32.76 -32.76   +0.89
2019-01-23      NaN -21.51 -21.51  +16.73
2019-01-24      NaN -26.18 -26.18   -5.94
2019-01-25      NaN -39.83 -39.83  -18.49
2019-01-28      NaN -38.08 -38.08   +2.92
2019-01-29      NaN -28.78 -28.78  +15.01
2019-01-30      NaN -34.64 -34.64   -8.23
2019-01-31      NaN -35.99 -35.99   -2.06
2019-02-01      NaN -37.90 -37.90   -2.99
2019-02-04      NaN -35.14 -35.14   +4.44
2019-02-05      NaN -46.92 -46.92  -18.16
2019-02-06      NaN -46.86 -46.86   +0.12
2019-02-07      NaN -36.26 -36.26  +19.94
2019-02-08      NaN -22.53 -22.53  +21.54
2019-02-11      NaN -26.95 -26.95   -5.70
2019-02-12      NaN -27.87 -27.87   -1.26
2019-02-13      NaN -28.09 -28.09   -0.31
2019-02-14      NaN -27.76 -27.76   +0.46
2019-02-15      NaN -33.14 -33.14   -7.45
2019-02-18      NaN -37.83 -37.83   -7.01
2019-02-19      NaN -29.26 -29.26  +13.79
2019-02-20      NaN -37.39 -37.39  -11.50
2019-02-21      NaN -43.57 -43.57   -9.88
2019-02-22      NaN -38.00 -38.00   +9.88
2019-02-25      NaN -45.07 -45.07  -11.40
2019-02-26      NaN -39.17 -39.17  +10.74
2019-02-27      NaN -41.16 -41.16   -3.27
2019-02-28      NaN -54.90 -54.90  -23.36
2019-03-01      NaN -65.22 -65.22  -22.87
2019-03-04      NaN -67.20 -67.20   -5.69
2019-03-05      NaN -61.14 -61.14  +18.47
2019-03-06      NaN -66.74 -66.74  -14.42
2019-03-07      NaN -51.25 -51.25  +46.60
2019-03-08      NaN -41.56 -41.56  +19.87
2019-03-11      NaN -51.20 -51.20  -16.50
2019-03-12      NaN -46.92 -46.92   +8.78
```

```
2019-03-13      NaN -53.26 -53.26  -11.94
2019-03-14      NaN -45.85 -45.85  +15.83
2019-03-15      NaN -46.18 -46.18   -0.61
2019-03-18      NaN -50.28 -50.28   -7.62
2019-03-19      NaN -56.08 -56.08  -11.67
2019-03-20      NaN -46.13 -46.13  +22.67
2019-03-21      NaN -40.62 -40.62  +10.22
2019-03-22      NaN -29.77 -29.77  +18.27
2019-03-25      NaN -23.65 -23.65   +8.72
2019-03-26      NaN -22.38 -22.38   +1.66
2019-03-27      NaN -25.04 -25.04   -3.44
2019-03-28      NaN -16.56 -16.56  +11.32
2019-03-29      NaN -31.20 -31.20  -17.55
2019-04-01      NaN -34.81 -34.81   -5.24
2019-04-02      NaN -35.90 -35.90   -1.68
2019-04-03      NaN -46.18 -46.18  -16.03
2019-04-04      NaN -50.39 -50.39   -7.82
2019-04-05      NaN -47.07 -47.07   +6.69
2019-04-08      NaN -40.13 -40.13  +13.10
2019-04-09      NaN -35.73 -35.73   +7.36
2019-04-10      NaN -45.77 -45.77  -15.62
2019-04-11      NaN -55.37 -55.37  -17.70
2019-04-12      NaN -67.44 -67.44  -27.05
2019-04-15      NaN -74.25 -74.25  -20.90
2019-04-16      NaN -89.25 -89.25  -58.27
2019-04-17      NaN -98.52 -98.52  -86.27
2019-04-18      NaN -97.05 -97.05  +99.63
2019-04-22      NaN -97.05 -97.05   +0.00
2019-04-23      NaN -94.19 -94.19  +97.24
2019-04-24      NaN -92.04 -92.04  +36.95
2019-04-25      NaN -86.51 -86.51  +69.59
2019-04-26      NaN -86.96 -86.96   -3.34
2019-04-29      NaN -88.11 -88.11   -8.85
2019-04-30      NaN -80.47 -80.47  +64.26
2019-05-01      NaN -75.49 -75.49  +25.51
2019-05-02      NaN -71.24 -71.24  +17.36
2019-05-03      NaN -60.52 -60.52  +37.23
2019-05-06      NaN -66.73 -66.73  -15.73
2019-05-07      NaN -49.09 -49.09  +53.04
2019-05-08      NaN -58.51 -58.51  -18.50
2019-05-09      NaN -38.55 -38.55  +48.11
2019-05-10      NaN -33.06 -33.06   +8.92
2019-05-13      NaN -30.97 -30.97   +3.12
2019-05-14      NaN -33.14 -33.14   -3.15
2019-05-15      NaN -24.16 -24.16  +13.44
2019-05-16      NaN -28.26 -28.26   -5.41
2019-05-17      NaN -25.16 -25.16   +4.32
2019-05-20      NaN -19.02 -19.02   +8.20
2019-05-21      NaN -17.15 -17.15   +2.32
2019-05-22      NaN -21.12 -21.12   -4.79
```

```
2019-05-23      NaN  -12.25  -12.25   +11.24
2019-05-24      NaN   -5.45   -5.45    +7.76
2019-05-27      NaN   +0.59   +0.59    +6.39
2019-05-28      NaN   +8.88   +8.88    +8.24
2019-05-29      NaN   +5.03   +5.03    -3.54
2019-05-30      NaN   -0.14   -0.14    -4.92
2019-05-31      NaN   -3.79   -3.79    -3.65
2019-06-03      NaN   +7.73   +7.73   +11.97
2019-06-04      NaN  -17.57  -17.57   -23.48
2019-06-05      NaN  -14.32  -14.32    +3.93
2019-06-06      NaN   -2.99   -2.99   +13.22
2019-06-07      NaN   +0.70   +0.70    +3.81
2019-06-10      NaN   -3.11   -3.11    -3.78
2019-06-11      NaN  -18.48  -18.48   -15.87
2019-06-12      NaN  -22.56  -22.56    -5.00
2019-06-13      NaN  -27.26  -27.26    -6.07
2019-06-14      NaN  -26.80  -26.80    +0.62
2019-06-17      NaN  -31.14  -31.14    -5.93
2019-06-18      NaN  -42.49  -42.49   -16.47
2019-06-19      NaN  -59.35  -59.35   -29.32
2019-06-20      NaN  -68.30  -68.30   -22.02
2019-06-21      NaN  -69.87  -69.87    -4.94
2019-06-24      NaN  -54.61  -54.61   +50.64
2019-06-25      NaN  -60.64  -60.64   -13.30
2019-06-26      NaN  -76.26  -76.26   -39.69
2019-06-27      NaN  -81.28  -81.28   -21.12
2019-06-28      NaN  -81.82  -81.82    -2.89
2019-07-01   +67.71   +0.00  -87.26      NaN
2019-07-02      NaN   +0.00  -87.26    +0.00
2019-07-03      NaN   +2.57  -86.93    +2.57
2019-07-04      NaN   -1.29  -87.42    -3.76
2019-07-05      NaN   +6.91  -86.37    +8.31
2019-07-08      NaN   +4.09  -86.73    -2.64
2019-07-09      NaN   +1.81  -87.02    -2.19
2019-07-10      NaN   -0.99  -87.38    -2.75
2019-07-11      NaN   -4.36  -87.81    -3.41
2019-07-12      NaN   -0.10  -87.27    +4.45
2019-07-15      NaN   +2.37  -86.95    +2.48
2019-07-16      NaN   -1.29  -87.42    -3.58
2019-07-17      NaN   -0.50  -87.32    +0.80
2019-07-18      NaN  -13.56  -88.98   -13.12
2019-07-19      NaN  -13.77  -89.01    -0.24
2019-07-22      NaN  -18.92  -89.67    -5.98
2019-07-23      NaN  -11.66  -88.74    +8.96
2019-07-24      NaN  -10.12  -88.54    +1.75
2019-07-25      NaN  -11.54  -88.73    -1.59
2019-07-26      NaN   -5.71  -87.98    +6.60
2019-07-29      NaN  -12.07  -88.79    -6.75
2019-07-30      NaN  -23.65  -90.27   -13.16
2019-07-31      NaN  -29.00  -90.95    -7.01
```

```
2019-08-01      NaN -39.51 -92.29  -14.80
2019-08-02      NaN -15.92 -89.28  +38.99
2019-08-05      NaN -18.67 -89.63   -3.27
2019-08-06      NaN -22.31 -90.10   -4.47
2019-08-07      NaN -31.30 -91.24  -11.57
2019-08-08      NaN -24.30 -90.35  +10.19
2019-08-09      NaN -28.34 -90.87   -5.34
2019-08-12      NaN -34.92 -91.71   -9.18
2019-08-13      NaN -28.07 -90.83  +10.53
2019-08-14      NaN -31.44 -91.26   -4.69
2019-08-15      NaN -35.27 -91.75   -5.57
2019-08-16      NaN -20.52 -89.87  +22.78
2019-08-19      NaN -15.35 -89.21   +6.50
2019-08-20      NaN -25.08 -90.45  -11.50
2019-08-21      NaN -22.38 -90.11   +3.61
2019-08-22      NaN  +0.53 -87.19  +29.52
2019-08-23      NaN  +7.77 -86.27   +7.20
2019-08-26      NaN  +9.04 -86.10   +1.19
2019-08-27      NaN  +8.55 -86.17   -0.45
2019-08-28      NaN  +5.18 -86.59   -3.10
2019-08-29      NaN +17.41 -85.04  +11.62
2019-08-30      NaN +19.36 -84.79   +1.66
2019-09-02      NaN +19.30 -84.79   -0.05
2019-09-03      NaN +23.23 -84.29   +3.29
2019-09-04      NaN +24.95 -84.07   +1.40
2019-09-05      NaN +31.82 -83.20   +5.49
2019-09-06      NaN +37.13 -82.52   +4.03
2019-09-09      NaN +50.57 -80.81   +9.80
2019-09-10      NaN +77.09 -77.43  +17.61
2019-09-11      NaN +77.88 -77.33   +0.44
2019-09-12      NaN +68.01 -78.59   -5.55
2019-09-13      NaN +77.66 -77.36   +5.74
2019-09-16      NaN +77.03 -77.44   -0.35
2019-09-17      NaN +62.14 -79.33   -8.41
2019-09-18      NaN +56.98 -79.99   -3.18
2019-09-19      NaN +62.36 -79.31   +3.42
2019-09-20      NaN +56.56 -80.05   -3.57
2019-09-23      NaN +51.35 -80.71   -3.33
2019-09-24      NaN +52.65 -80.54   +0.86
2019-09-25      NaN +62.59 -79.28   +6.51
2019-09-26      NaN +44.98 -81.52  -10.83
2019-09-27      NaN +41.21 -82.00   -2.60
2019-09-30      NaN +36.96 -82.54   -3.01
2019-10-01      NaN +42.28 -81.87   +3.88
2019-10-02      NaN +39.97 -82.16   -1.62
2019-10-03      NaN +28.51 -83.62   -8.19
2019-10-04      NaN +21.54 -84.51   -5.43
2019-10-07      NaN +29.12 -83.54   +6.24
2019-10-08      NaN +24.42 -84.14   -3.64
2019-10-09      NaN +17.60 -85.01   -5.48
```

```
2019-10-10      NaN +23.57 -84.25   +5.08
2019-10-11      NaN +48.41 -81.09  +20.10
2019-10-14      NaN +39.59 -82.21   -5.94
2019-10-15      NaN +45.91 -81.40   +4.53
2019-10-16      NaN +49.19 -80.99   +2.25
2019-10-17      NaN +34.75 -82.83   -9.68
2019-10-18      NaN +22.33 -84.41   -9.22
2019-10-21      NaN +33.85 -82.94   +9.41
2019-10-22      NaN +32.66 -83.09   -0.89
2019-10-23      NaN +44.55 -81.58   +8.96
2019-10-24      NaN +49.67 -80.92   +3.55
2019-10-25      NaN +48.97 -81.01   -0.47
2019-10-28      NaN +41.10 -82.02   -5.28
2019-10-29      NaN +37.61 -82.46   -2.47
2019-10-30      NaN +36.02 -82.66   -1.15
2019-10-31      NaN +29.32 -83.52   -4.93
2019-11-01      NaN +25.88 -83.96   -2.66
2019-11-04      NaN +34.92 -82.80   +7.18
2019-11-05      NaN +36.95 -82.55   +1.51
2019-11-06      NaN +41.83 -81.92   +3.57
2019-11-07      NaN +57.33 -79.95  +10.93
2019-11-08      NaN +56.59 -80.04   -0.47
2019-11-11      NaN +48.95 -81.02   -4.88
2019-11-12      NaN +36.87 -82.56   -8.11
2019-11-13      NaN +39.96 -82.16   +2.25
2019-11-14      NaN +42.87 -81.79   +2.08
2019-11-15      NaN +43.82 -81.67   +0.66
2019-11-18      NaN +73.42 -77.90  +20.58
2019-11-19      NaN +77.49 -77.38   +2.35
2019-11-20      NaN +75.19 -77.67   -1.30
2019-11-21      NaN +72.00 -78.08   -1.82
2019-11-22      NaN +83.54 -76.61   +6.71
2019-11-25      NaN +95.10 -75.13   +6.30
2019-11-26      NaN +88.86 -75.93   -3.20
2019-11-27      NaN +83.02 -76.67   -3.09
2019-11-28      NaN +83.97 -76.55   +0.52
2019-11-29      NaN +83.37 -76.63   -0.32
2019-12-02      NaN +89.57 -75.84   +3.38
2019-12-03      NaN +78.80 -77.21   -5.68
2019-12-04      NaN +84.72 -76.46   +3.31
2019-12-05      NaN +91.11 -75.64   +3.46
2019-12-06      NaN +96.76 -74.92   +2.96
2019-12-09      NaN +98.31 -74.73   +0.79
2019-12-10      NaN +87.30 -76.13   -5.55
2019-12-11      NaN +84.93 -76.43   -1.27
2019-12-12      NaN +84.89 -76.44   -0.02
2019-12-13      NaN +91.35 -75.61   +3.49
2019-12-16      NaN +96.30 -74.98   +2.59
2019-12-17      NaN +78.72 -77.22   -8.96
2019-12-18      NaN +76.16 -77.55   -1.43
```

```
2019-12-19      NaN +73.02 -77.95    -1.78
2019-12-20      NaN +63.04 -79.22    -5.77
2019-12-23      NaN +75.95 -77.57    +7.92
2019-12-24      NaN +77.58 -77.37    +0.92
2019-12-25      NaN +77.58 -77.37    +0.00
2019-12-26      NaN +77.58 -77.37    +0.00
2019-12-27      NaN +77.74 -77.35    +0.09
2019-12-30      NaN +72.19 -78.05    -3.12
2019-12-31      NaN +67.71 -78.63    -2.60
```

Listing I.9: Qrumble's daily measures for the Buying Winners and Selling Losers strategy in the MKTP in 2019.

# ANNEX II

| **2015** | **ROI % (annual)** | **Mean %** | **St Dev %** | **Sharpe** | **Beta** | **Alpha %** | **VaR/1y %** | **TVaR/1y %** |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 6.68 | 7.85 | 17.67 | 0.48 | 0.93 | -1.71 | 28.08 | 39.24 |
| **VWP** | *5.21* | *6.54* | 17.89 | 0.40 | *0.95* | *-3.20* | 27.46 | 39.59 |
| **MVP** | **11.76** | **12.1** | **16.01** | **0.79** | 0.73 | **4.92** | **24.07** | **33.96** |
| **MKTP** | 7.2 | 11.42 | *30.51* | *0.39* | **0.67** | 4.88 | *40.87* | *72.13* |
| **2016** | | | | | | | | |
| **EWP** | 18.18 | 17.52 | 15.53 | 1.17 | 0.77 | 9.67 | 23.72 | 31.29 |
| **VWP** | **21.88** | **20.61** | 16.01 | **1.32** | *0.78* | **12.64** | 23.65 | 32.33 |
| **MVP** | 15.63 | 15.23 | **14.48** | 1.09 | 0.48 | 10.68 | **20.45** | **29.45** |
| **MKTP** | *-59.62* | *-68.97* | *62.26* | *-1.1* | **0.4** | *-74.67* | *93.06* | *150.96* |
| **2017** | | | | | | | | |
| **EWP** | 8.48 | 8.52 | 10.71 | 0.85 | *1.11* | -4.04 | **16.01** | **19.76** |
| **VWP** | 8.53 | 8.52 | **10.28** | **0.89** | 1.04 | -3.27 | 16.26 | 19.95 |
| **MVP** | *1.92* | *2.39* | 10.37 | *0.29* | **0.79** | *-6.55* | 16.04 | 23.36 |
| **MKTP** | **9.98** | **10.18** | *17.39* | 0.62 | 0.84 | **0.88** | *27.85* | *40.67* |
| **2018** | | | | | | | | |
| **EWP** | -12.02 | -11.63 | **13.25** | -0.83 | 0.96 | -3.48 | 23.21 | **30.62** |
| **VWP** | **-11.79** | **-11.36** | 13.34 | -0.81 | **0.95** | **-3.30** | **21.83** | 30.71 |
| **MVP** | -15.06 | -14.96 | 13.97 | *-1.03* | 0.99 | -6.69 | 23.71 | 32.62 |
| **MKTP** | *-23.48* | *-22.21* | *28.01* | **-0.77** | *1.32* | *-11.39* | *49.97* | *62.88* |
| **2019** | | | | | | | | |
| **EWP** | 19.01 | 17.57 | 11.23 | **1.62** | *0.84* | -0.89 | **16.16** | **23.98** |
| **VWP** | 17.72 | 16.50 | **11.14** | 1.53 | *0.84* | -2.06 | 17.72 | 24.27 |
| **MVP** | *15.01* | *14.27* | 11.51 | *1.29* | 0.82 | *-3.84* | 17.6 | 26.33 |
| **MKTP** | **95.45** | **82.51** | *59.34* | 1.4 | **-0.13** | **88.39** | *84.0* | *111.58* |
| **Total** | | | | | | | | |
| **EWP** | 43.2 (7.45/1y) | 7.97 | 13.93 | **0.62** | 0.88 | -0.56 | 22.35 | 30.58 |
| **VWP** | **44.51 (7.64/1y)** | **8.17** | 14.03 | **0.62** | *0.89* | **0.25** | 21.60 | 30.83 |
| **MVP** | 28.67 (5.17/1y) | 5.82 | **13.42** | 0.48 | 0.7 | -3.05 | **20.72** | **29.95** |
| **MKTP** | *-29.26 (-6.69/1y)* | *2.65* | *43.44* | *0.07* | **0.61** | *-14.63* | *68.59* | *101.82* |

Table II.1: Yearly and total results of the Dogs of the Dow investment strategy for five years.

| 2015 | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 5.65 | 5.06 | 15.78 | 0.36 | 0.11 | 4.52 | 24.98 | **31.65** |
| **VWP** | 4.51 | 4.87 | **15.21** | 0.36 | **-0.04** | 6.0 | 25.69 | 32.52 |
| **MVP** | **31.01** | **27.67** | **15.21** | **1.86** | 0.55 | **22.81** | **20.56** | 35.81 |
| **MKTP** | *-123.44* | *-624.19* | *562.01* | *-1.11* | *2.37* | *-664.84* | *431.6* | *1355.15* |
| **2016** | | | | | | | | |
| **EWP** | -0.16 | 3.75 | 25.92 | 0.17 | -0.32 | 8.17 | 42.79 | 55.05 |
| **VWP** | -6.06 | -0.49 | 27.99 | 0.0 | *-0.9* | 10.49 | 50.54 | 63.29 |
| **MVP** | *-9.47* | *-8.66* | **18.94** | *-0.43* | 0.45 | *-13.42* | **29.12** | **40.84** |
| **MKTP** | **1.6** | **25.46** | *72.53* | **0.36** | **-0.14** | **28.19** | *94.75* | *149.29* |
| **2017** | | | | | | | | |
| **EWP** | 1.58 | 2.28 | 12.25 | 0.23 | 0.56 | -3.89 | 20.67 | 24.75 |
| **VWP** | -0.89 | -0.16 | 12.01 | 0.04 | **0.35** | -3.81 | 19.85 | 24.87 |
| **MVP** | **12.61** | **12.19** | **10.85** | **1.18** | 0.46 | **7.55** | **17.18** | **22.35** |
| **MKTP** | *-82.69* | *-3682.44* | *2984.0* | *-1.23* | *-8.46* | *-3667.12* | *801.17* | *6027.76* |
| **2018** | | | | | | | | |
| **EWP** | **-2.25** | **-1.42** | **12.65** | *-0.06* | 0.16 | 0.41 | **20.29** | 29.81 |
| **VWP** | -6.65 | -5.72 | 14.12 | -0.36 | **0.15** | *-4.0* | 24.79 | 32.56 |
| **MVP** | -7.0 | -6.29 | **12.65** | -0.45 | 0.6 | -0.93 | 21.65 | **29.52** |
| **MKTP** | *-106.76* | **705.14** | *709.54* | **0.99** | *2.81* | **608.59** | *568.0* | *1336.54* |
| **2019** | | | | | | | | |
| **EWP** | 7.08 | 7.34 | 14.84 | 0.54 | 0.55 | -4.8 | 25.4 | 32.82 |
| **VWP** | -4.94 | *-3.85* | 11.67 | *-0.28* | 0.41 | *-12.9* | 18.52 | 27.81 |
| **MVP** | **18.6** | 16.23 | **11.5** | **1.46** | **0.39** | 8.08 | **15.21** | **22.0** |
| **MKTP** | *-78.63* | **289.93** | *275.62* | 1.05 | *-3.7* | **383.57** | *290.94* | *502.31* |
| **Total** | | | | | | | | |
| **EWP** | 12.16 (2.32/1y) | 3.4 | 17.0 | 0.24 | **0.06** | 15.03 | 26.68 | 38.02 |
| **VWP** | -13.65 (-2.89/1y) | -1.07 | 17.25 | -0.03 | -0.2 | 4.86 | 26.01 | 40.3 |
| **MVP** | **47.32 (8.06/1y)** | **8.24** | **14.14** | **0.63** | 0.5 | **18.96** | **22.32** | **32.02** |
| **MKTP** | *-321.37 (-217.22/1y)* | *-169.88* | *1319.32* | *-0.13* | *-3.63* | *-695.71* | *369.69* | *1373.6* |

Table II.2: Yearly and total results of the Buying Winners and Selling Losers investment strategy for five years.

| 2015 | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | *14.47* | *15.15* | 20.02 | 0.79 | 0.94 | 5.74 | 32.42 | 44.09 |
| **VWP** | 16.11 | 16.92 | 21.85 | 0.8 | *1.13* | *5.43* | 34.75 | 48.97 |
| **MVP** | 19.01 | 18.59 | *18.21* | **1.05** | 0.81 | 10.65 | **25.96** | **36.58** |
| **MKTP** | **31.1** | **53.07** | **73.08** | *0.73* | **-0.07** | **55.92** | *117.05* | *164.65* |
| **2016** | | | | | | | | |
| **EWP** | 29.92 | 28.68 | 25.07 | **1.17** | **0.77** | 21.1 | 37.95 | **47.14** |
| **VWP** | 27.1 | 26.38 | 24.35 | 1.11 | 1.02 | 15.85 | *36.69* | 54.6 |
| **MVP** | *19.11* | *20.01* | **24.2** | 0.85 | 1.08 | *8.57* | 39.72 | 58.2 |
| **MKTP** | **159.53** | **369.35** | *490.65* | *0.75* | *5.17* | **318.95** | *642.64* | *1213.08* |
| **2017** | | | | | | | | |
| **EWP** | 4.41 | 5.61 | 16.76 | 0.37 | 1.04 | -6.2 | 27.77 | 35.09 |
| **VWP** | 9.0 | 9.83 | 16.86 | 0.62 | 1.39 | -6.21 | 23.77 | 30.45 |
| **MVP** | *-2.71* | *-1.64* | **14.48** | *-0.07* | **1.02** | *-13.39* | **23.73** | **29.65** |
| **MKTP** | **92.7** | **212.97** | *175.94* | **1.21** | *4.27* | **166.98** | *244.81* | *349.71* |
| **2018** | | | | | | | | |
| **EWP** | -6.54 | -4.95 | 18.18 | -0.24 | 1.21 | 5.39 | 34.3 | 42.13 |
| **VWP** | -6.94 | -5.27 | 18.77 | *-0.25* | *1.24* | 5.33 | 33.04 | 42.13 |
| **MVP** | **2.51** | **3.57** | **15.16** | **0.27** | **0.91** | **11.68** | **27.53** | **36.11** |
| **MKTP** | *-14.32* | *-9.05* | *34.83* | -0.24 | *1.24* | *1.39* | *54.86* | *72.91* |
| **2019** | | | | | | | | |
| **EWP** | 19.51 | 18.36 | 14.28 | 1.33 | 1.02 | -4.19 | 24.11 | 33.08 |
| **VWP** | *15.55* | *15.12* | 14.57 | 1.08 | 1.01 | *-7.37* | 25.26 | 34.82 |
| **MVP** | **24.64** | 22.16 | **12.04** | **1.89** | **0.77** | **5.33** | **17.72** | **25.58** |
| **MKTP** | 20.42 | **67.43** | *99.6* | *0.68* | *3.73* | *-16.92* | *178.49* | *204.36* |
| **Total** | | | | | | | | |
| **EWP** | 73.44 (11.64/1y) | 12.58 | 19.19 | 0.69 | 0.94 | 20.31 | 31.71 | 41.29 |
| **VWP** | *72.96 (11.58/1y)* | 12.6 | 19.57 | 0.67 | 1.11 | *12.26* | 30.99 | 43.31 |
| **MVP** | 76.19 (11.99/1y) | *12.55* | **17.31** | **0.76** | **0.92** | 20.97 | **26.21** | **38.95** |
| **MKTP** | **576.49 (46.57/1y)** | **148.6** | *269.54* | *0.55* | *2.73* | **632.68** | *223.40* | *545.74* |

Table II.3: Yearly and total results of the F_score investment strategy for five years.

| 2015 | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 18.91 | *18.08* | 15.67 | 1.19 | 0.82 | *10.02* | 24.67 | 33.36 |
| **VWP** | 22.56 | 21.5 | 18.50 | 1.19 | 0.97 | 11.94 | 29.07 | 40.26 |
| **MVP** | **30.73** | **27.2** | **14.99** | **1.85** | **0.62** | **21.69** | **22.38** | **28.39** |
| **MKTP** | *15.88* | 22.52 | *40.5* | *0.57* | *1.14* | 11.02 | *66.55* | *94.49* |
| **2016** | | | | | | | | |
| **EWP** | 8.14 | 9.22 | 17.73 | 0.55 | *0.93* | -0.72 | 26.25 | 44.87 |
| **VWP** | **11.79** | **12.07** | **15.38** | **0.82** | 0.77 | **4.02** | **24.35** | **34.49** |
| **MVP** | -4.76 | *-3.27* | 17.26 | *-0.15* | 0.62 | *-9.87* | 25.84 | 44.58 |
| **MKTP** | *-6.22* | 3.92 | *45.39* | 0.1 | **0.41** | -0.09 | *71.03* | *93.45* |
| **2017** | | | | | | | | |
| **EWP** | *10.99* | *10.56* | **8.69** | *1.28* | 0.85 | *1.09* | **13.09** | **19.88** |
| **VWP** | 14.81 | 13.90 | 9.03 | 1.61 | 0.84 | 4.71 | 16.69 | 20.03 |
| **MVP** | 14.92 | 14.12 | 10.4 | **1.42** | **0.61** | 7.65 | 15.83 | 22.65 |
| **MKTP** | **162.23** | **192.95** | *141.32* | 1.37 | *5.19* | **135.29** | *232.92* | *286.78* |
| **2018** | | | | | | | | |
| **EWP** | *-18.81* | *-19.44* | 13.48 | *-1.40* | 0.97 | *-11.38* | 25.97 | 32.34 |
| **VWP** | -15.82 | -15.94 | 13.17 | -1.17 | 0.91 | -8.33 | 23.83 | 31.18 |
| **MVP** | -15.19 | -15.38 | **11.95** | -1.24 | **0.81** | -8.58 | **21.35** | **29.14** |
| **MKTP** | **9.18** | **13.38** | *31.03* | **0.45** | *0.99* | **22.32** | *48.37* | *71.34* |
| **2019** | | | | | | | | |
| **EWP** | 24.95 | 22.6 | 13.62 | 1.70 | 1.16 | *-3.12* | 20.83 | 31.46 |
| **VWP** | 27.79 | 24.67 | **12.63** | **2.0** | 0.99 | 2.89 | 18.86 | 27.26 |
| **MVP** | *22.51* | *20.63* | 13.31 | 1.59 | **0.65** | 6.75 | **18.09** | **24.89** |
| **MKTP** | **52.04** | **79.1** | *88.6* | *0.9* | *2.38* | **26.45** | *126.85* | *162.95* |
| **Total** | | | | | | | | |
| **EWP** | *44.77 (7.68/1y)* | *8.22* | 14.17 | *0.62* | 0.93 | *-1.24* | 22.54 | 33.39 |
| **VWP** | 69.22 (11.09/1y) | 11.26 | 14.10 | **0.84** | 0.89 | 16.01 | 22.36 | 31.73 |
| **MVP** | 48.66 (8.25/1y) | 8.69 | **13.81** | 0.67 | **0.65** | 14.16 | **21.36** | **30.46** |
| **MKTP** | **373.03 (36.45/1y)** | **62.36** | *80.59* | 0.78 | *1.3* | **258.27** | *114.51* | *182.09* |

Table II.4: Yearly and total results of the Magic Formula investment strategy for five years.

| 2015 | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 16.95 | 16.71 | 17.18 | 1.01 | *0.89* | 7.91 | 25.37 | 37.46 |
| **VWP** | **17.76** | **17.38** | 17.16 | **1.05** | 0.88 | **8.64** | 24.91 | 37.28 |
| **MVP** | 9.94 | 10.49 | **15.96** | 0.7 | 0.64 | 4.23 | **24.29** | **36.36** |
| **MKTP** | *-5.48* | *-3.78* | *18.48* | *-0.17* | **0.59** | *-9.87* | *29.29* | *38.69* |
| **2016** | | | | | | | | |
| **EWP** | 16.59 | 16.88 | **19.39** | 0.9 | 0.99 | 6.45 | 29.24 | **44.29** |
| **VWP** | 17.07 | 17.30 | 19.48 | **0.92** | *1.0* | 6.78 | 28.88 | 44.65 |
| **MVP** | *-7.14* | *-5.0* | 20.94 | *-0.21* | **0.77** | *-13.44* | **25.05** | 51.66 |
| **MKTP** | **30.67** | **36.12** | *44.82* | 0.82 | 0.9 | **27.23** | *69.7* | *100.21* |
| **2017** | | | | | | | | |
| **EWP** | 25.55 | 22.73 | **10.00** | 2.33 | 0.85 | 13.6 | **15.50** | 20.29 |
| **VWP** | **26.20** | 23.24 | 10.02 | **2.38** | *0.86* | 14.04 | 15.86 | **20.26** |
| **MVP** | *12.01* | *11.81* | 12.08 | 1.03 | **0.63** | *5.02* | 16.72 | 24.28 |
| **MKTP** | 24.39 | **27.3** | *34.68* | *0.8* | 0.75 | **19.49** | *49.43* | *72.86* |
| **2018** | | | | | | | | |
| **EWP** | -4.82 | -3.92 | 13.47 | -0.25 | 0.87 | 3.69 | 24.21 | 32.85 |
| **VWP** | **-4.52** | **-3.63** | **13.39** | **-0.23** | 0.87 | **3.97** | 23.68 | 32.59 |
| **MVP** | -9.99 | -9.38 | 13.42 | -0.65 | **0.83** | -2.22 | **22.9** | **31.71** |
| **MKTP** | *-32.44* | *-35.56* | *23.32* | *-1.5* | *0.97* | *-27.91* | *41.48* | *54.53* |
| **2019** | | | | | | | | |
| **EWP** | 34.16 | 29.27 | 11.56 | 2.58 | 0.78 | 12.50 | 17.79 | 22.49 |
| **VWP** | **34.33** | 29.39 | 11.48 | **2.61** | 0.78 | 12.73 | 17.68 | **22.24** |
| **MVP** | 27.8 | *24.46* | **10.81** | 2.32 | **0.66** | *10.28* | **15.59** | 22.62 |
| **MKTP** | *-11.7* | **45.31** | *106.94* | *0.43* | *-1.15* | **74.07** | *160.26* | *235.0* |
| **Total** | | | | | | | | |
| **EWP** | 118.58 (16.93/1y) | 16.34 | **14.73** | 1.15 | *0.9* | 41.49 | 22.29 | 33.15 |
| **VWP** | **123.14 (17.41/1y)** | **16.74** | **14.73** | **1.18** | *0.9* | 43.5 | **22.16** | **33.07** |
| **MVP** | 31.55 (5.64/1y) | *6.49* | 15.07 | 0.47 | 0.72 | *-0.2* | 22.18 | 34.41 |
| **MKTP** | *-8.35 (-1.73/1y)* | 13.89 | *55.72* | *0.26* | **0.55** | **45.48** | *76.42* | *136.52* |

Table II.5: Yearly and total results of the Liquid Median Dogs of the Dow investment strategy for five years.

| **2015** | **ROI % (annual)** | **Mean %** | **St Dev %** | **Sharpe** | **Beta** | **Alpha %** | **VaR/1y %** | **TVaR/1y %** |
|---|---|---|---|---|---|---|---|---|
| **EWP** | *16.41* | *16.29* | 17.4 | 0.97 | 0.92 | **7.09** | 29.46 | 36.72 |
| **VWP** | 18.56 | 18.58 | 20.09 | 0.95 | **1.08** | 7.65 | 32.31 | 43.1 |
| **MVP** | 30.17 | 26.76 | **14.8** | **1.85** | **0.67** | 20.69 | **22.32** | **31.45** |
| **MKTP** | **40.92** | **57.0** | *68.75* | *0.84* | 0.74 | **51.05** | *105.72* | *166.45* |
| **2016** | | | | | | | | |
| **EWP** | **21.95** | 21.1 | **18.46** | **1.18** | 0.96 | 11.05 | 27.26 | **44.07** |
| **VWP** | 19.45 | 19.19 | 19.05 | 1.04 | 0.99 | 8.82 | **26.97** | 44.3 |
| **MVP** | *-16.9* | *-15.34* | 23.26 | *-0.63* | **0.86** | *-25.0* | 34.31 | 58.24 |
| **MKTP** | -10.68 | **201.87** | *217.34* | 0.93 | *2.4* | **179.47** | *291.48* | *434.37* |
| **2017** | | | | | | | | |
| **EWP** | *9.76* | *9.43* | *8.1* | 1.24 | 0.76 | *1.11* | **12.58** | **17.88** |
| **VWP** | 15.69 | 14.64 | 8.98 | **1.7** | 0.79 | 6.0 | 15.1 | 18.95 |
| **MVP** | 10.41 | 10.32 | 11.37 | *0.96* | **0.6** | 3.89 | 18.07 | 26.1 |
| **MKTP** | **63.97** | **54.21** | **34.36** | 1.6 | *0.84* | **45.94** | *47.71* | *72.06* |
| **2018** | | | | | | | | |
| **EWP** | *-12.39* | *-12.06* | 13.11 | -0.87 | 0.98 | -3.78 | 23.68 | 28.62 |
| **VWP** | -11.66 | -11.38 | 12.11 | *-0.89* | 0.89 | *-3.79* | **23.50** | **28.1** |
| **MVP** | -6.41 | -5.78 | **11.74** | -0.44 | **0.79** | 1.1 | 19.97 | 26.13 |
| **MKTP** | **23.21** | **24.72** | *29.5* | **0.86** | *1.17* | **35.46** | *44.22* | *63.55* |
| **2019** | | | | | | | | |
| **EWP** | 25.28 | 22.67 | 12.13 | 1.92 | 1.03 | *-0.15* | 18.98 | 27.91 |
| **VWP** | **26.29** | 23.22 | **10.07** | **2.36** | 0.74 | 7.17 | 16.36 | **21.09** |
| **MVP** | 19.97 | *18.24* | 10.19 | 1.85 | **0.58** | 5.95 | **15.92** | 21.41 |
| **MKTP** | *-585.62* | **3925.28** | *2739.59* | *1.43* | *3.23* | **3959.62** | *1324.43* | *2835.0* |
| **Total** | | | | | | | | |
| **EWP** | 71.03 (11.33/1y) | 11.5 | **14.34** | 0.84 | 0.95 | 14.52 | 23.19 | **33.3** |
| **VWP** | **82.78 (12.82/1y)** | 12.86 | 14.8 | **0.91** | *0.96* | 20.85 | 23.67 | 34.15 |
| **MVP** | 34.12 (6.05/1y) | *6.87* | 15.05 | *0.5* | 0.73 | *1.0* | **22.0** | 35.16 |
| **MKTP** | *-1334.85 (-265.32/1y)* | **765.15** | *1305.85* | 0.59 | **0.66** | **3892.33** | *749.99* | *1763.88* |

Table II.6: Yearly and total results of the Flowy Formula investment strategy for five years.

| 2015 | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 30.51 | 27.24 | 16.28 | 1.71 | 0.82 | 19.49 | **23.98** | 34.14 |
| **VWP** | **32.23** | **28.6** | 16.8 | **1.74** | *0.85* | **20.54** | 26.28 | 36.15 |
| **MVP** | 24.78 | *22.86* | **16.21** | 1.45 | **0.66** | *16.73* | 25.52 | **34.13** |
| **MKTP** | *24.64* | 23.69 | *21.27* | *1.14* | 0.7 | 17.15 | *32.3* | *47.23* |
| **2016** | | | | | | | | |
| **EWP** | 11.67 | 12.31 | 17.46 | 0.74 | *0.86* | 3.27 | 26.93 | 44.52 |
| **VWP** | **22.43** | **20.89** | **15.0** | **1.43** | 0.68 | **14.09** | **23.49** | **30.92** |
| **MVP** | 3.72 | *4.69* | 15.02 | 0.35 | **0.53** | -0.74 | 24.57 | 35.06 |
| **MKTP** | *3.56* | 6.39 | *24.32* | *0.29* | 0.71 | *-1.07* | *36.56* | *62.91* |
| **2017** | | | | | | | | |
| **EWP** | 21.41 | 19.51 | **10.54** | **1.91** | 0.94 | 9.19 | **16.99** | **21.71** |
| **VWP** | 25.72 | 23.32 | 13.88 | 1.72 | *1.0* | 12.41 | 22.1 | 27.65 |
| **MVP** | *10.87* | *10.68* | 10.95 | *1.03* | **0.69** | *3.16* | 17.33 | 22.69 |
| **MKTP** | **51.17** | **43.59** | *25.41* | 1.74 | 0.74 | **36.29** | *39.02* | *47.8* |
| **2018** | | | | | | | | |
| **EWP** | *-14.64* | *-14.2* | 15.86 | *-0.86* | 1.11 | *-4.89* | 28.76 | 37.22 |
| **VWP** | -13.51 | -12.85 | 16.29 | -0.75 | *1.13* | -3.32 | *31.12* | 38.73 |
| **MVP** | **-4.45** | **-3.48** | **13.91** | **-0.21** | 0.97 | **4.91** | **26.06** | **33.34** |
| **MKTP** | -8.72 | -7.48 | *16.92* | -0.41 | **0.93** | 0.49 | 26.99 | *39.91* |
| **2019** | | | | | | | | |
| **EWP** | 31.42 | 27.87 | 15.99 | 1.78 | *1.27* | *-0.41* | 24.12 | 34.59 |
| **VWP** | 29.69 | 26.34 | 14.4 | **1.87** | 1.16 | 0.56 | 21.68 | 30.94 |
| **MVP** | *23.96* | *21.78* | **13.24** | 1.69 | **0.98** | 0.22 | **21.52** | **28.55** |
| **MKTP** | **79.07** | **66.78** | *45.11* | *1.49* | 1.01 | **45.74** | *66.69* | *84.6* |
| **Total** | | | | | | | | |
| **EWP** | 98.48 (14.69/1y) | 14.56 | 15.42 | 0.98 | *0.94* | 30.47 | 23.86 | 35.47 |
| **VWP** | 128.27 (17.95/1y) | 17.28 | 15.32 | **1.17** | 0.89 | 46.86 | 24.06 | 33.53 |
| **MVP** | *69.95 (11.19/1y)* | *11.32* | **13.97** | *0.85* | **0.71** | *24.95* | **22.77** | **31.61** |
| **MKTP** | **218.9 (26.1/1y)** | **26.62** | *28.34* | 0.96 | 0.78 | **99.88** | *40.15* | *61.92* |

Table II.7: Yearly and total results of the Magical Bambu investment strategy for five years.

| Total | ROI % (annual) | Mean % | St Dev % | Sharpe | Beta | Alpha % | VaR/1y % | TVaR/1y % |
|---|---|---|---|---|---|---|---|---|
| **EWP** | 135.39 (18.68/1y) | 17.72 | 14.28 | 1.28 | 0.87 | 49.88 | 21.3 | 31.12 |
| **VWP** | 136.85 (18.82/1y) | 17.84 | 14.23 | **1.3** | 0.87 | 50.66 | 20.88 | 31.03 |
| **MVP** | 58.0 (9.58/1y) | 10.08 | 15.31 | 0.7 | 0.64 | 22.08 | 20.32 | 31.48 |
| **MKTP** | **357.21 (35.53/1y)** | **102.92** | *365.95* | *0.28* | *0.91* | **485.12** | *85.56* | *339.35* |

Table II.8: Total results of the Median Dogs of the Dow investment strategy for five years.