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Quality Factor in the European Stock Market

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1. INTRODUCTION

This is a research thesis aimed at investigating market anomalies. The idea is to investigate market anomalies, implement an investment strategy, using a programming language through a quantitative analysis and back test the strategy over the last 20 years in the European stock market. There is an extensive literature with examples of how to earn excess return and exploit anomalies in the market, but it is only in the recent period such an interest in the factor investing. Factor investing is a strategy that chooses firms based on characteristics that are associated with subsequent abnormal returns. The recent development is because this investment methodology is based on simple and economically sensible criteria. In the future it will be increasingly applied and evolve with the use of Big Data. In addition, factor investing has taken off to contain the high costs of active portfolio managers while maintaining management techniques used by them but at lower costs. It is a kind of mix between passive and active management, where passive management is a style management based on mutual or exchange traded fund (ETF). According to the Efficient Market Hypothesis (EMH), a market is efficient because all market prices reflect all available information. This theory has received criticism since some anomalies exist and markets are not correctly priced. Anomalies such as small-firm-in January effect, book-to-market and price to earnings are popular findings in the finance literature. In the light of this, I wanted to explore a market anomaly that is present but not fully defined: the quality factor. The results achieved by

the various portfolios, that will be examined and analysed in detail, are surprisingly positive. In the Long Only strategy, the results show a clear outperformance compared to the overall market in the European stock market with a Sharpe ratio for Cap-weighted portfolio and equally weighted portfolio respectively of 0,63 and 0,66. In the Long-Short strategy, the portfolios outperformed the benchmark in terms of risk adjusted return (0,63 compared to 0,53). Market capitalization weighted and equally weighted are the main weighting scheme used in this work. Moreover, the Jensen's Alpha generated by the two strategies is positive and high: it reaches 6% in the Long-Short while in the Long Only is 5%.

1.1 Purpose and Structure of the study

This thesis aims to investigate whether the quality factor is a real premium factor and whether there is an anomaly in the market. The focus of the analysis will be on the European market since, despite the extensive literature in the US, there is no in-depth study of empirical asset pricing.

Since the factor has multiple shades with different variables to be included within the model, as we will see later, the purpose of the investigation is to see which ones are the best at explaining future stock returns, i.e the best at predicting the returns.

The factor's world is full of literature from top academics and articles from major investment funds since the 60s. Despite many indices from the best investment funds around the world, there is no precise definition of quality. The challenge of this work is to find the variable with the best explanatory power at predicting future stock returns.

The analysis is carried out using a common methodology in empirical asset pricing, which is called Univariate Portfolio Analysis. After the proper selection of the variable, the thesis work will be to build a stock portfolio and back test it to see how it performs over time. The aim is to see if it has a positive alpha and if there is an extra return, in relation to different benchmarks.

I will implement the study by analysing the data from Refinitiv Eikon Data Provider and by using Python, as the main programming language, together with Microsoft Excel. Every year, I rank the European companies, from the Stoxx Europe 600, in order of some criteria of profitability, earnings stability and capital structure. The top 10 percent of the companies are selected into the long-only portfolio and the bottom 10 percent are selected in the short portfolio. I also construct a long-short portfolio, a portfolio that is sometimes difficult to implement for retail investors but is extremely important to test the performance of the factor. For this reason, from a client investor's

perspective, first I will present the Long-Only strategy, which seems to be simpler to implement in terms of constraints. The Long-Short portfolio is part of a market neutral strategy that aims to seek profit from increasing and decreasing prices, while avoiding any kind of market specific risks.

As Fama and French indicates from their papers, the start date of the holding period is the last trading date of June for each year. The data are available from 1999 until 2021 and the portfolio formation is based on the previous year.

After the creation of the portfolios, an analysis of each of them is made through Excel with different tools. An average annual return, an annualized standard deviation and a Sharpe ratio are calculated to have risk-adjusted returns and to compare the performance with the benchmarks.

Then, a statistical test is done by regression analysis. It is a useful tool to assess the existence of an alpha, after controlling for various premium factors. It is also a way to find the source of the returns earned by the portfolio through a simple OLS regression.

Moreover, a further strategy and its possible developments will be discussed. The strategy consists of a mix of value and quality, two factors which, as we will see, seem to work well together, both theoretically and practically.

Lastly, a detailed analysis of sectors and turnover will be carried out to assess how they might affect performance.

In conclusion, two potential explanations will be discussed. One is related with the risk and the efficient market hypothesis and other one is related with the behavioural finance and the investor optimism.

2. FACTOR INVESTING

Factor investing has become increasingly popular for over 20 years among both equity and fixed-income investor who have realised that they could have increased the desired exposure, reduce risk, increase return.

A factor can be thought of as a characteristic of an aggregate of assets that is important in explaining return and risk. To be better understood, I describe the factor quoting an author[1], through an analogy, “the factors are to assets what nutrients are to foods”.

The popularity was driven also by successful investors such as Warren Buffett, Seth Klarman and Joel Greenblatt. Thereafter, academic research has proliferated. As shown in Graph 1[2], from an article by famous academics, the number of papers and factors have grown rapidly over time, with strong increase in the last twenty years. Graph 1 includes only the factors documented by the top academic journals. Over 400 factors have been presented until the end of year 2018 and the number continues to increase over time.

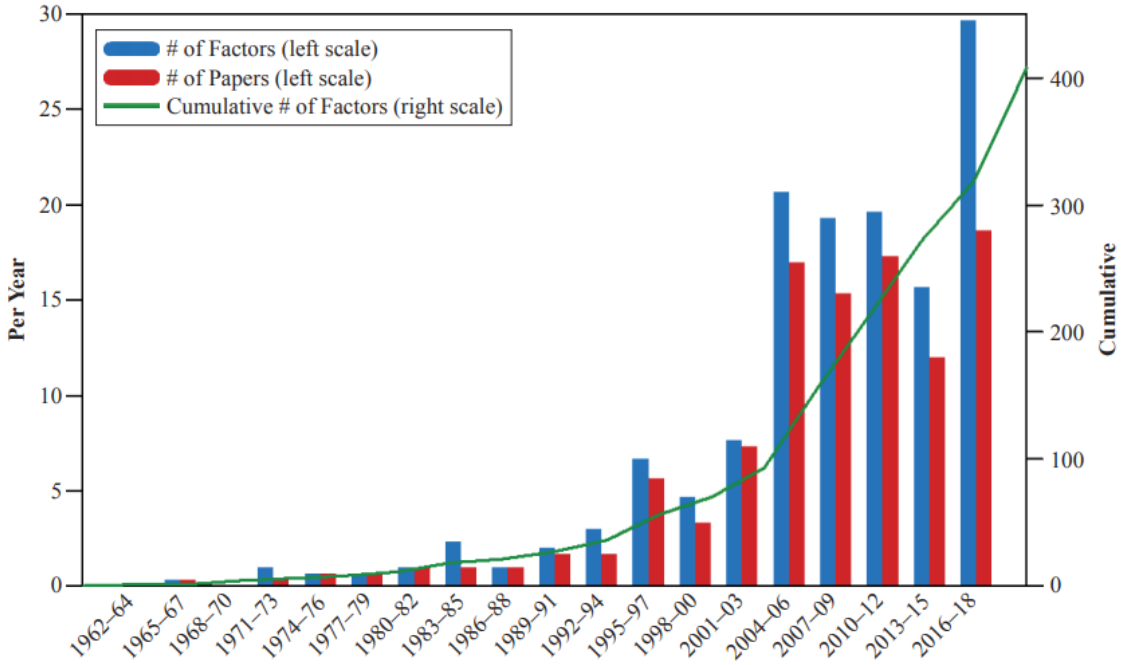
GRAPH 1

The picture is the results of an analysis carried out by Harvey, Liu, and Zhu (2016) and it was updated by R.Arnott, C.R.Harvey, V.Kalesnik, J. Linnainmaa in ‘ Alice’s Adventures in Factorland: Three Blunders that plague factor investing in 2019.

[1] Andrew Ang, ‘Asset Management: A systematic approach to factor investing’, 2014

[2] R.Arnott, C.R.Harvey, V.Kalesnik, J. Linnainmaa, ‘ Alice’s Adventures in Factorland: Three Blunders that plague factor investing, 2019

Factors and Publication Years, Limited to Top-Tier Academic Journals



Source: Harvey and Liu (2019).

It is a relatively new concept that is rapidly spreading, and it is based on factors premium, for example value, momentum and volatility in equity market, that have demonstrated to be robust over time and across different markets.

There are different types of factors:

1. Macroeconomic Factors
    - GDP growth, inflation and volatility
2. Cross Sectional Factors
    - Size, Value and Momentum
3. Statistical Factors
    - Derived empirically from the covariance matrix

Although the birth of the factors dates back to 1960, the real turning point of the recent period is the publication of the *Evaluation of Active Management of the Norwegian Government Pension Fund – Global* report in 2009. This paper discusses the performance of one of the world's largest sovereign wealth funds after the Financial Crisis of 2007-2008.

Created by three top academics, Andrew Ang, William Goetzmann and Stephen Schaefer, the report demonstrate that the abnormal return of the fund's active managers did not prove their real ability. Rather, this alpha could be explained by the large exposure to some factors. Based on their findings, they suggested a long-term strategy incorporating an exposure to proven factors to maximize risk-adjusted returns.

Some estimates of the amount of money invested in factor-based strategies are controversial and vary from 1 to 2 trillion globally. In a paper released in 2019, Blackrock estimated that factor industry is almost USD 1.9 trillion and the factor-based and quant strategies are projected to grow to 3.4 trillion by 2022. Additionally, in a paper published in 2017, Morgan Stanley estimated that assets under management (AUM) have increased by 17% per year on average since 2010.

For this reason, factor investing is no longer a product reserved for a niche but is accessible to all. It is used by both the world's largest institutional investors and retail investors who have access to hundreds of products, such as the world of ETFs.

From a survey by asset manager Invesco in 2018, factor exposure accounted for approximately 16% of total portfolio allocations of institutional asset owners having adopted factor investing. According to a survey by FTSE Russell, 48% of asset owners around the world have implemented factor-based strategies, in their portfolios in 2018.

From Invesco (2020), in another survey about factor allocations changes, almost 97% of investors plan to maintain or increase the factor exposures the next year and only 30% are disappointed about performance of factor strategies. There is a vast literature in the field of factors premium.

Otherwise, some critics came from Arnott, Beck, and Kalesnik (2016) who showed that the performance of a factor vanishes after publication.

Moreover, transaction costs play a key role. Novy-Marx and Velikov (2016) demonstrate that almost no factor, constructed as a long–short portfolio, with turnover above 50%, produces abnormal return in excess of the trading costs.

The earliest theory of factor investing was the Capital Asset Pricing Model (CAPM), (Lintner, 1965; Mossin, 1966; Sharpe, 1964 and Treynor, 1961) which argued that there was only one driver of stock returns, and the factor is the Beta, or the sensitivity of the expected stock return to equity market return. In the CAPM, securities have only two main drivers, systematic risk and

idiosyncratic risk. The former is the risk, captured by the Beta, and is derived from the exposure to the market. Since it cannot be diversified, investors are remunerated with returns for assuming the risk.

$$E(R_i) = R_f + \beta_a\,(E(R_m - R_f))$$

Where:

- $E(R_i)$ is the expected return of an asset *i*
- R_f is the risk free rate
- $E(R_m)$ is the expected return of the market
- β_a is the beta of the given asset with respect to the market. It is the systematic risk of a stock in comparison to the market. It is calculated as the covariance of a stock with the market, all divided by the variance of the market. $\beta = \frac{Cov\,(R_i, R_m)}{Var\,(R_m)}$

In 1972, Haugen and Heins refined the CAPM in order to create the low volatility factor investing, showing that the companies with lower volatility tend to earn higher return.

A decade later, a research paper by Stephen A. Ross in 1976 demonstrates that security returns are explained by various factors, introducing the Arbitrage Pricing Theory (APT). From that moment on, literature has been enriched with examples and papers explaining different factors.

APT formula is as follows:

$$E(R_i) = R_f + \beta_{i1}\,RP_1 + \beta_{i2}\,RP_2 + \ldots + \beta_{kn}\,RP_n$$

Where:

- $E(R_i)$ is the expected return of an asset *i*
- R_f is the risk free rate

- β_i is the sensitivity of a given asset in relation to the risk premium
- RP is the risk premium of the specified factor

2.1 Size Factor (SMB)

The size factor refers to the fact that companies with small market capitalization tend to outperform companies with large market capitalization.

In 1981, Rolf Banz found that smaller company stocks outperform larger company over 40 years with a 0.4% premium per month (Banz, 1981, "Returns and firm size").

This anomaly can be explained by the concept of distress risk, according to which companies with small caps suffers from liquidity and economic problem, and higher returns are the reward for investing in these companies. Moreover, most of This factor is used in the Fama French model and it is called Small Minus Big (SMB).

2.2 Value Factor (HML)

In addition to the size effect, there is another relationship between an investment strategy and long-term performance. A value stock is a stock with relatively low price to book multiple, high dividend yields or high earnings to price. Growth stocks are the opposite of value stocks, the price is relatively high because the stock market discounts all the future cash flows, reflecting a prosperous future of the business. Investors have demonstrated that stocks with low price earnings ratios are more likely to be undervalued and earn excess returns. Conversely, stocks with low earnings to price mean that investors are paying more for earnings and the implied expectations for future earnings growth are larger. This was one of Benjamin Graham primary's screens.

In 1983, Basu found evidence for earnings yield with a 0.6% premium per month for cheap stocks ("The Relationship Between Earnings Yield, Market Value and Return for NYSE Common Stocks").

In 1992, Eugene Fama and Kenneth R. French showed that company size and valuation factor were drivers of stock price. The credit of Fama and French was to add to the CAPM, two additional factors, such as size(SMB) and value (HML which is High Minus Low)

2.3 Momentum Factor (WML)

This factor reflects the higher expected return of stocks that have performed positively in the 12 months preceding the observation period, relative to contrarian stocks, i.e. stocks with securities with a weak performance. According to this investment strategy, stocks that have performed well are likely to outperform those stocks that have performed bad in the next 12 months.

In 1993, in "Returns to buying winners and selling losers", Jeegadesh and Titman showed average monthly excess return to buy winners and sell losers and this holds across size and beta, but it is stronger in small caps and high beta stocks.
The Momentum Factor (WML which stands for Winners Minus Losers) is included in the Carhart Four Factor Model (1997).

2.4 Profitability Factor (RMW)

Profitable firms often generate significantly higher returns than unprofitable firms, despite having higher valuation ratios. In fact, companies with high profitability are more expensive than others but, despite this, historically the returns are higher.

Eugene Fama and Kenneth French (2004)[3] argued that firms with high profitability measured by earnings ratio have high subsequent returns after controlling for book-to-market ratio and investment, compared to companies with low profitability.
The profitability factor is called Robust Minus Weak, built by Fama and French.

2.5 Investment Factor (CMA)

Research shows that the investment factor has explanatory power for the cross section of stock returns. High investment firms tend to underperform low investment firms. Risk-based arguments shows that firms with growth options are riskier than firms that have converted growth options into assets. The first are Conservative firms (with low asset growth) and the latter are Aggressive firms (with high asset growth). Behavioural finance arguments suggest that investors overreact to

3 Eugene Fama and Kenneth French, 'Profitability, Growth, and Average Returns', 2004.

transient asset-growth rates and then to be disappointed when returns revert to a normal level. Fama French 5-Factor Model includes CMA factor in the model.

2.6 Defensive factor-The Low Beta Anomaly (BAB)

The low beta anomaly is that low beta stocks have higher returns than high beta stocks.

Frazzini A. and Pedersen L. in Betting Against Beta (2014)[4] show that high beta assets deliver subsequent lower return than low beta assets. They developed a model where investors face leverage and margin constraints. Constrained investors choose high beta assets and bid up their prices. This is demonstrated by Black[5], who showed that the gradient of the Security Market Line is lower than the theoretical of the CAPM

2.7 Macroeconomic Factor

All those securities that are influenced by non-diversifiable factors affecting the level of consumption should earn a risk premium in economies where individuals are risk averse.

In 1986, Chen, Ross and Roll found that Macroeconomic Factors can systematically affect stock market returns. Their model considers unexpected movements in industrial production, inflation and expected inflation movements, risk premia and expected inflation movements, risk premia, interest rate maturity structure, market indices rates, market indices, consumption levels and crude oil prices price of crude oil.

2.8 Liquidity Factor

In 1986, Amihud and Mendelson found a positive relation between the bid-ask spread, which is a measure of illiquidity, and expected stock returns. In other words, the expected stock returns increase as the liquidity of the share decreases.

3. QUALITY FACTOR

3.1 Literature Review

After a brief review of how the interest in factor investing has considerably increased in the recent decades, the quality factor is one of the strongest and most scalable reported anomalies in capital markets. It refers to the tendency of high-quality stocks with stable earnings and cash flows, sound balance sheet, higher margin to outperform low-quality stocks over long term. Researchers

[4] Frazzini, Petersen,'Betting Against Beta',2014.
[5] Black, F. ,'Studies of Stock Price Volatility Changes', 1976.

Assness and Frazzini[6] define the quality factor as investing in the stocks of safe, profitable, expanding and well-managed companies or all those "characteristics that make a company valuable".

Quality investing starts in 1930s when Benjamin Graham, the father of value investing and the greatest financial consultant in 1900s, divided high quality companies and low-quality stocks and distinguished between cheap and quality stocks.

As he has stated on several occasions, Buffett is inspired by Benjamin Graham. His strategy is to buy cheap, safe and high- quality stocks. He is considered the father of what can be called "quality investing at a good price", with this referring to the value dimension. Warren Buffett realized an average annual return of 18,6%, outperforming the stock market's return of 7,5%[7]. One dollar invested in 1976 would have been worth almost 4000$ today. The surprisingly performance should not be confused with lucky but with a targeted stock selection. This can be demonstrated by the alpha that becomes insignificant when you control the exposures for "quality minus junk" and "betting against beta". The results of Warren Buffett appear to be a reward for investing in high-quality companies.

In 1996, Richard G. Sloan found that firms with low levels of accruals and high levels of cash flows experience positive future excess stock returns[8]. Accruals are revenues earned or expenses incurred which impact company's earnings, although the payment hasn't received or made yet. The analysis of the accruals is critical to assess the manipulation of the earnings and, thus, the quality of them.

After the Dot-Com Bubble in 2001, quality factor became increasingly popular as investor started to pay more attention to the quality of earnings, sound balance sheet, information transparency, good management team etc... This is the reason why a well-managed quality strategy provides great protection from the risk faced by value investors. Sometimes, companies are cheap for a specific reason and the Dot-Com Bubble highlighted this negative side.

[6] Clifford S. Asness, Andrea Frazzini, and Lasse H. Pedersen: 'Quality Minus Junk', 2013
[7] Andrea Frazzini, David Kabiller, CFA, and Lasse Heje Pedersen, 'Buffet's Alpha', 2018
[8] Richard G. Sloan, 'Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? ', 1996

In 2013, Robert Novy Marx found that the profitability, calculated by gross profits to assets, has explanatory power to predict cross section of returns. This means that profitable firms generate excess returns compared to unprofitable firms[9].

In 2017, Ferhat Akbas, professor in the university of Illinois at Chicago, showed that the trend in gross profitability predicts future earnings growth and stock returns[10].

In academia, Eugene Fama and Kenneth French introduced the quality premium with the operating profitability factor, calculated as revenues minus cost of goods sold divided by the book value of equity. The top quintile significantly outperformed other quintiles by 5,5% from 1990 to 2019.

The quality factor is usually identified as an autonomous source of return, that also aid to diversify the portfolio due to the low correlation with other factors, value and momentum. However, according to Hsu, Kalesnik, and Kose (HKK)[11] the quality factor lacks definitions, compared to well-known and accepted value, size, and momentum factors. They have studied that the factor is able to provide a wide use of measures to distinguish for good and bad quality companies. They illustrate how index providers implicitly define the quality factors, by looking at what variables some indices consist of. The analysis, based on six major quality indices, has shown that quality variables include return on equity, dividend growth, change in asset turnover, and debt-to-cash flow ratio, among others. Overall, these diverse attributes fall into seven groups: profitability, earnings stability, capital structure, growth, accounting quality, payout/dilution, and investment.

Leverage, accruals and investment are considered evidence of managerial conservatism. From these analyses of the indices, the author has demonstrated that the most robust metrics are related to profitability, investments, and conservative accounting and issuance policy.

Their study in the literature was able to show that variables, such as profitability, investment (i.e. asset growth), accounting quality, and payout/dilution, are strongly correlated with future returns. Regarding capital structure, the empirical results are doubtful, but a deeper look may reveal that these are also related to the low-beta anomaly. Moreover, earnings stability is also considered a

[9] Robert Novy Marx, 'The other side of value: The gross profitability premium', The Journal of Financial Economics, 2013

[10] F. Akbas, C. Jiang and P.D. Koch, 'The trend in Firm Profitability and the Cross Section of Stock Returns', The accounting Review, 2017

[11] Jason Hsu, Vitali Kalesnik , and Engin Kose, 'What is quality?', 2019

factor and low beta. Finally, HKK found that the most correct quality definition is a combination of the profitability and investment signals.

There is no definition of quality because some relate it to financial indicators, other relate it to non-financial indicators. For instance, some refer it to sustainable practices. The main reason is that quality is entirely based on accounting and reporting data while other factors are based on a market data or on a mix of market and accounting data[12]. Since reporting data are many, the quality can be classified in many ways. In a survey, Feng et Al (2020[13]), where are illustrated 150 factors, more than half can be related to quality factor. This gives you an idea of how broad the scope of possibilities is.

Another reason why there is not a standard definition is that quality factor is constructed differently from other factors. The value and momentum are created from a particular stock feature or a combination of them to capture a risk premium with an undiversifiable economic risk. For example, while value is constructed taking high earning yield (Earnings per Share / Price per Share) companies, high book to market ratio or high dividend yield (Dividend per Share / Price per Share) or a combination of them, quality factor portfolios are created in different ways as there are not accepted measures. One can take companies that has high score or a combination in: earnings growth, earnings growth stability, low return volatility, high profitability, high return on assets, low debt ratio, and accruals-related accounting quality. In addition, the definition is more disperse than other factors

Georgi Kyosev, Matthias X. Hanauer, Joop Huij, and Simon Lansdorp found that quality indicators can predict future stock returns if they have good connection with future earnings growth. Quality variables which don't have explanatory power for future earnings growth also have no explanatory power for the cross-section of future stock returns. Thus, the predictive power of quality indicators for stock returns can be linked to their predictive power for future earnings growth[14].

4. HOW TO BUILD A QUALITY FACTOR

For the reasons described before, the choice of the variables that will be included in the Quality is not an easy task. In this chapter, it will be illustrated how and why the variables are chosen among

[12] Amundi Asset Management, Frédéric Lepetit, Amina Cherief. Yannick Ly, Takaya Sekine, 'Revising Quality Investing', 2021
[13] Feng, G., Giglio, S., and Xiu, D., 'Taming the Factor Zoo: a Test of New Factors', Journal of Finance, 2020
[14] Georgi Kyosev, Matthias X. Hanauer, Joop Huij, and Simon Lansdorp, 'Does Earnings Growth Drive the Quality Premium?', Robecco Quality, 2020

other. I started with the MSCI definition of quality as a mix of profitability, stable earnings, and low debt.

These characteristics are:

-Return On Equity (ROE), a good proxy for the profitability, measured by company's net income divided by its total shareholders' equity. This formula can be decomposed in Return on Assets (ROA) and the amount of financial leverage. $ROE = \frac{Net\ Income}{Total\ Shareholders'\ Equity}$

- Year over Year Earnings (YoYearnings), a proxy of earnings variability, measured by actual revenues – past revenues, all divided by past revenues. It tells you how sales are stable over time.

$$YoY\ Earnings = Variance[\frac{(Earnings_t - Earnings_{t-1})}{Earnings_{t-1}}]$$

- Debt- to- Equity, a proxy of financial leverage, calculated by company's total debt divided by its total shareholders' equity

MSCI quality index combines these three fundamental variables to obtain an average Z-Score and then rank all the companies based on their quality score. The methodology in this thesis is the same of MSCI Quality Index, but the main difference is that the variables are all back tested to see the relation and the ability of them to predict future stock returns.

According to Grantham[15], quality is defined by taking an average score of ROE, the inverse of ROE volatility and assets-to-book.

Damodaran in 2004 stated that investors can define quality with those characteristics related to corporate governance, credit rating and ethical issues.

Other investors can look at the ESG criteria (Environment-Social-Governance), which is becoming so popular in the recent years that some Investment Funds started to create ETF ad hoc.

Friede, Busch and Bassen (2015) carried out an analyis using 2,200 empirical studies, showing that huge numbers of the papers establish a positive relationship between ESG and financial performance.

15 Grantham, J.' The Case for Quality – The Danger of Junk'. GMO White Paper, 2004

For example, Hanson and Dhanuka, in 2015, combined quality investing with these criteria[16]. They analysed sustainability practices, corporate culture and Environmental-Social Governance (ESG) practices and stated that they could yield an abnormal return.

Greenblatt, in 2006, presented a formula which consists of the earnings yield measured as EBIT/EV and return on invested capital (ROIC)[17]. The latter is a quality indicator while the former is a value indicator.

Piotroski[18] used nine accounting-based variables that account for quality. These indicators are proxies for profitability, operating efficiency, liquidity.

Blackrock, the largest asset manager in the world, when constructing the quality factor, uses the accruals approach proposed by Sloan (1996) as I discussed above.

The Earnings Quality Factor proposed by MSCI [19] is a composite of three descriptors, calculated and standardized, two of them are related to accruals and one is cash earnings to earnings. Cash Earnings focus on a firm's cash revenues less cash expenses and exclude accruals. Then, the indicators are combined to produce a score. High score means that the company has low accruals, high operating cash flows and high cash earnings.

In addition, the quality strategy should be careful not to overpay stocks because of their extraordinary profitability and tendency to be expensive. For this reason, Mead, Sage and Citro (2013)[20], stated that a Value component is necessary to implement a quality strategy, and the combination of both criteria is the best strategy to yield long-term abnormal return.

As the reader can understand, the building of this factor is far away from other factors such as value, size and momentum. In this thesis, I decided to examine future return predictability of each variable through the portfolio analysis, one of the most common methodology in empirical asset pricing. The aim is to find a cross sectional relation between one variable, taken from the vast literature I presented above, and the future stock returns (1-year ahead return), in order to

16 Dan Hanson and Rohan Danuka, 'The Science and Art of High-Quality Investing, 2015
17 Joel Greenblatt, 'The little book that beats the market, 2006
18 Piotroski, J.D.' Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers'. Journal of Accounting Research,2000
19 John Regino, Leon Roisenberg and Daniel Young, 'Introducing the earnings quality factor', 2016
20 Katrina Mead,Jonathan Sage, and Mark Citro, 'Quality and Value: The Essence of Long Term Equity Return', 2013

choose properly and to construct a quality factor. In the next section, this will be discussed in detail.

4.1 Univariate Portfolio Analysis

The univariate portfolio analysis is the most common methodology used in asset pricing to find a cross-sectional relation between two variables. Most of the time, the application of this technique is to demonstrate the ability of one variable to predict future stock returns. The approach is to create portfolios of stocks, based on some breakpoints. It is a nonparametric technique; thus, it doesn't make any assumptions about the relation of the two variables (it could be either liner or nonlinear). Otherwise, the main downside is that this analysis is difficult to carry out when large numbers are taken into consideration while regression analysis is more appropriate and more reliable.

A univariate portfolio analysis has only one sort variable *(X)* and the aim is to establish a relation between the *X* and the outcome variable *(Y).* In this analysis, the outcome variable *Y* is the future stock returns, and the independent variable *X* changes every time the analysis is carried out. It has four steps. The first step is to calculate the breakpoints that will be used to divide the sample into portfolios. The second step is to form the portfolios. The third step is to calculate the returns, as the average values of the outcome variable *Y* within each portfolio for each period *t.* The fourth step is to examine the variations in these average values across different portfolios.

4.1.1 Breakpoints

The first step is to calculate the periodic breakpoints, used to create the portfolios. These are calculated based on seven percentile (10^{th}, 20^{th}, 40^{th}, 60^{th}, 80^{th}, 90^{th}). For each year, the breakpoints are used to divide the portfolios. Stocks, that are below the values associated with the 10^{th} decile, falls into the first decile (the bottom decile or the bottom portfolio). Stocks with values between the 10^{th} and 20^{th} breakpoints form the second decile portfolio and so on. At the end, stocks with higher values form the last portfolio (the top portfolio or top decile). The value of the *kth* portfolio changes over time, for each time period. So, the breakpoints are calculated for each year, semester, month, depending on the portfolio rebalancing.

4.1.2 Portfolio Formation

For each year, seven portfolios are created. The first portfolio is formed with stocks with values less than the value of the 10th breakpoints, portfolio two with stocks with values between the 10th and 20th breakpoints, and, finally, portfolio seven (top portfolio) with values greater than the value of the 90th breakpoints. The number of stocks varies across portfolios as less companies have extreme values and, thus, the majority is included in 40th and 60th portfolios.

4.1.3 Average Portfolio Values

The third step is to calculate the average of the outcome variable *Y* and, in this analysis, the average returns in each time period for each portfolio. The returns are calculated according two different weighting schemes, equally weighted and value weighted, in order to be more robust and consistent with empirical asset pricing procedure.

4.1.4 Summarizing the Results

This analysis is aimed to see the difference in values between bottom and top portfolio, whether there is an excess return. To do so, an average time series is calculated for each portfolio as well as for the difference portfolio (top minus bottom portfolio).

The time-series average is the estimates of the true average values of the outcome variable for stocks in each of the portfolios in the average time period. In addition to this, it is useful to see whether the average is statistically significant different from zero. A statistically nonzero mean is evidence that the cross-sectional relation between Y and X exists.

5. DATA

In this chapter, the data and methodology are presented for testing the variables and constructing quality portfolios.

5.1 Global Universe

In this section, the data collection, that will be the sample, is covered in detail.

The academic study for premium factors is based on broad universe, for example all listed companies in each region. Some of those companies are characterized by the difficult to trade because they are very small and are very illiquid. This analysis is focused on 600 companies in the Stoxx Europe 600, an index composed by large, mid and small capitalization companies among 17 European countries, which covers 90% of the overall capitalization in the European market. This

reflects the choice to analyse the quality factor in European market, as most of the researchers has been focused on American market. It was introduced in 1998, so the analysis starts with 1999 in order to have more screened data and due to the unavailability of the data. A long history is the prerequisite to demonstrate an alpha or the existence of a factor premium. In this thesis, the data are from 1999 July to 2020 July.

5.2 Data Sources

The companies included have been retrieved from Thomson Eikon Refinitiv. Every year, within the index, some companies are delisted and other are listed. This could be a complexity but, through Eikon Data API, it is able to retrieve actual companies included in the Stoxx EU 600 for each different year.

6. FACTOR ANALYSIS

In order to properly choose the factor, I carried out an analysis with the methodology, explained in detail above, considering the main drivers for profitability, investment, capital structure, earnings quality, efficiency and growth according to the literature.

6.1 Profitability Factor – Analysis ROE, ROA and Gross Profit-to-Assets

Profitability is the most used for the construction of quality portfolio. The literature is full of article from the top academics, and all found a positive premium on profitability. The first indicators are profitability ratios with a focus on ROE and ROA. The first takes into account debt, while the latter doesn't. If a company doesn't carry debt, ROA and ROE will be equal because equity and assets will be equal.

6.1.1 Return on Equity (ROE) and Stock Returns

I begin the examination of the variables with the univariate portfolio analysis between Return on Equity (ROE) and future stock returns. This is the main profitability factor, used in MSCI quality index. The breakpoints are calculated for all companies in the Stoxx Europe 600. The portfolios are constructed by sorting on ROE and are value-weighted in Panel A, using market capitalization of each of the companies. In Panel B the portfolios are equally weighted. The results[21], presented in Table 1 Panel A, indicate a negative relation between ROE and one year ahead stock returns of -4,27% but statistically insignificant (the t-statistics is only 1,3). The returns decrease monotonically from 8,41% per year for the low-ROE portfolio to 4,15% per year for the high-ROE portfolio. For a

[21] The table is an example of how the analysis has carried out and for the sake of brevity and clarity, the rest of the univariate analyses will be summarised in only average excess return and t-statistics

robustness check, I performed the analysis using an equal weighted scheme and Panel B presents a positive relation with an average excess return of the long-short portfolio of 2,05% per year, statistically significant at 95% level.

TABLE 1 Univariate portfolio analysis

This table presents the results of univariate portfolio analysis of the relation between ROE and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using ROE decile breakpoints calculated using all stocks in the sample. Panel A shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. Panel B presents the results for equally weighted portfolios. The analysis is carried out using the same breakpoints and the same decile as of cap- weighted. The numbers are in percentage.

Panel A : Value Weighted Portfolio sorting by ROE

Year	*Next Year*	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
giu-1999	giu-2000	33,811	71,215	66,886	28,838	18,289	27,715	-6,096
giu-2000	giu-2001	-27,996	-6,864	0,07	-16,038	-19,479	-5,531	22,466
giu-2001	giu-2002	-17,986	-23,407	-23,167	-15,591	-10,81	-26,64	-8,654
giu-2002	giu-2003	-8,115	-23,502	-19,723	-23,986	-28,416	-35,095	-26,981
giu-2003	giu-2004	8,036	11,883	18,767	41,025	23,834	20,065	12,03
giu-2004	giu-2005	15,443	11,505	21,128	19,004	19,138	9,801	-5,642
giu-2005	giu-2006	15,455	18,737	23,117	22,154	14,417	17,528	2,073
giu-2006	giu-2007	42,324	18,516	27,657	29,772	45,908	34,101	-8,224
giu-2007	giu-2008	-9,603	-12,02	-3,447	-18,055	-19,344	-13,704	-4,101
giu-2008	giu-2009	-21,113	-28,016	-30,733	-35,738	-28,873	-37,278	-16,165
giu-2009	giu-2010	23,615	13,711	11,203	24,73	22,345	16,37	-7,245
giu-2010	giu-2011	20,32	12,758	12,971	17,572	18,51	18,979	-1,341
giu-2011	giu-2012	-3,659	-20,99	-13,985	-15,938	-20,547	-22,576	-18,916
giu-2012	giu-2013	20,421	28,152	23,585	26,452	24,569	35,347	14,926
giu-2013	giu-2014	18,288	13,654	18,266	11,658	11,86	17,066	-1,222
giu-2014	giu-2015	35,814	16,854	6,689	8,182	13,038	3,526	-32,288
giu-2015	giu-2016	-5,702	-14,53	-12,18	-6,689	-10,29	-13,326	-7,624
giu-2016	giu-2017	-4,88	18,245	19,733	17,45	15,179	22,304	27,184
giu-2017	giu-2018	-3,388	-0,251	9,462	9,37	5,816	-0,387	3,002
giu-2018	giu-2019	-5,09	1,328	2,587	-10,292	-2,046	-2,859	2,231
giu-2019	giu-2020	23,64	19,441	0,262	0,095	-8,197	-11,296	-34,936
giu-2020	giu-2021	35,425	37,365	33,746	36,861	24,127	37,068	1,643
Average		8,41	7,45	8,77	6,86	4,96	4,15	-4,27
Std Error		4,04	4,63	4,36	4,34	4,08	4,53	3,14
T-Stat		2,08	1,61	2,01	1,58	1,21	0,91	1,36

Panel B : Equally Weighted Portfolio sorting by ROE								
Year	*Next Year*	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
giu-1999	giu-2000	28,9	22,9	19,2	25	17	28,1	-0,8
giu-2000	giu-2001	-12,7	4,3	3,4	0,6	3,7	-5,2	7,5
giu-2001	giu-2002	-18,6	-20,7	-9	-8,6	-7	-12,9	5,7
giu-2002	giu-2003	-34,1	-28,1	-23,6	-21,6	-20,9	-20,1	14
giu-2003	giu-2004	33,5	28,9	28,5	22,5	23,8	26	-7,4
giu-2004	giu-2005	8,5	24,3	17,1	19,7	24,7	16,4	7,8
giu-2005	giu-2006	28	29,6	22,3	26,3	21,2	26,5	-1,5
giu-2006	giu-2007	36	33,1	32,2	36,1	29,3	31,8	-4,2
giu-2007	giu-2008	-27,7	-21,3	-20,1	-23	-13	-8,8	18,9
giu-2008	giu-2009	-35,8	-27,9	-34,3	-30,5	-32,1	-27,2	8,6
giu-2009	giu-2010	18,4	17,7	19,4	19,4	24	26,7	8,3
giu-2010	giu-2011	27	20,1	17,3	14,9	20,3	23	-4
giu-2011	giu-2012	-28,3	-30,8	-25,6	-19,8	-12,7	-13,7	14,6
giu-2012	giu-2013	45,5	40,4	41	34,9	27,6	28,4	-17,1
giu-2013	giu-2014	31,4	24,4	15,7	15,9	13,2	6,7	-24,7
giu-2014	giu-2015	12,7	10,3	13,2	12,5	14,1	10,3	-2,5
giu-2015	giu-2016	-19,8	-11,8	-8,8	-6,8	-4,8	-6,3	13,5
giu-2016	giu-2017	25,4	17,9	25	15,9	23,2	23,9	-1,5
giu-2017	giu-2018	5	12	3,4	1,7	7,2	5,7	0,7
giu-2018	giu-2019	-5,4	-9,8	-11,2	-6,5	-5,6	-6,6	-1,2
giu-2019	giu-2020	-7,1	-7,8	-11,5	-4,7	1,5	8,2	15,3
giu-2020	giu-2021	36,3	50,6	38,8	33,3	33,4	31,3	-5
Average		6,69	8,10	6,93	7,15	8,55	8,74	2,05
Std Error		5,24	3,42	3,10	2,84	2,57	2,64	0,98
T-Stat		1,28	2,37	2,23	2,51	3,33	3,31	2,09

In summary, the results are not robust when using value or equally weighted. I repeated the analysis using monthly returns and there is no evidence or significance about the cross-sectional relation. As can be seen from the table 1, I failed to detect a positive relation between ROE, a profitability variable, and expected stock returns.

This variable is not able to predict abnormal returns and for this reason I choose ROA, that explains better the future returns than ROE.

6.1.2 Return on Assets (ROA) and Stock Returns

In this section, there is the relation between ROA and future stock returns. As can be seen in Table 2, returns of two portfolios are presented. This time, there is evidence and statistical significance about abnormal returns. Panel A shows an average Cap weighted return of 5,93% per year, with a T-statistics of 2,14, meaning that is statistically significant at 95% level. In Panel B, the average excess return is 6,65% per year (t-statistics of 3,02), statistically significant at 99% level. The returns are increasing monotonically from low-ROA portfolio to high-ROA portfolio, except for the second portfolio (80th percentile).

TABLE 2 This table presents the results of univariate portfolio analysis of the relation between ROA and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using ROA decile breakpoints calculated using all stocks in the sample. **Panel A** shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. **Panel B** presents the results for equally weighted portfolios. The analysis is carried out using the same breakpoints and the same decile as of cap- weighted. The numbers are in percentage.

Panel A: Value Weighted Portfolio Returns sorting by ROA

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Excess Returns	1,15	7,28	7,41	5,63	6,04	7,06	5,93
T-Statistics	0,23	1,45	1,68	1,44	1,75	2,57	2,14

Panel B: Equally Weighted Portfolio Returns sorting by ROA

Month Next	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Excess Returns	1,62	3,94	6,81	8,30	9,22	8,27	6,65
T-Statistics	0,34	0,93	1,80	2,18	2,82	2,72	3,02

In conclusion, I decided to choose ROA as the main profitability ratio to be included in the Quality definition, because ROA is more robust, and it explains better the returns in magnitude than ROE.

6.2 Investment Factor- Changes in Total Assets and CapEx Growth

The literature shows that companies with a conservative level of investment have higher returns. Fama and French added in their FFC model (Fama French Carhart) an investment factor called Conservative Minus Aggressive. CMA is the average return on the two conservative investment

portfolios minus the average return on the two aggressive investment portfolios. A good proxy for investment is the changes in total assets.

6.2.1 Change in Total Assets and Stock Returns

As you can see in the table 3 below, the average excess return sorting on changes in Total Assets is only 0,21% and it is not statistically significant. The values are not increasing from bottom to top portfolio and this means that there is no clear pattern of abnormal returns on this specific Investment Factor.

TABLE 3 This table presents the results of univariate portfolio analysis of the relation between Changes in Total Assets and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using Changes In Total Assets decile breakpoints calculated using all stocks in the sample. Table 3 shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. The numbers are in percentage.

Value Weighted Portfolio returns sorting by Changes in Total Assets

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	5,57	3,18	3,01	4,92	6,83	5,78	0,21
T-Stat	1,34	0,86	0,81	1,49	1,96	1,88	0,07

6.3 Earnings Stability – Y-o-Y Earnings

Earnings stability is used as a proxy for earnings persistency as indicator of quality. It tells you how smooth the growth of earnings was. I calculated the earnings stability using the same approach of MSCI as the standard deviation of year over year earnings growth over the last fiscal year. Findings shows that low anomalies in earnings growth are associated with investor optimism and with higher returns[22].

22 Hsu, Jason C. and Kudoh, Hideaki and Yamada, Toru. 'When Sell-Side Analysts Meet High-Volatility Stocks: An Alternative Explanation for the Low-Volatility Puzzle '. Journal of Investment Management, 2012

6.3.1 Year over Year Earnings growth and Stock Returns

The following Table 4 indicates that the portfolio with the lowest YoY earnings variability (the top portfolio) significantly outperform on average the highest earnings variability (the bottom portfolio). Panel A and Panel B shows that the average excess return per year is respectively 9,91% (t-stat 2,42) and 9,05% (t-stat 5,04). Both of the weighted scheme is statistically significant and, after the robustness check, the standard deviation of Year over Year Earnings growth over the last year is included in the Quality Factor. It seems to be an autonomous source of return that can be related to the low-beta effects.

TABLE 4 Univariate portfolio analysis

This table presents the results of univariate portfolio analysis of the relation between YoY earnings variability and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using the standard deviation year over year of earnings decile breakpoints calculated using all stocks in the sample. Panel A shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. Panel B presents the results for equally weighted portfolios. The analysis is carried out using the same breakpoints and the same decile as of cap- weighted. The numbers are in percentage.

Panel A: Value Weighted Portfolio Returns sorting by YoY earnings

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Excess Returns	1,56	4,11	2,81	6,35	7,47	11,47	9,91
T-Stat	0,45	1,31	1,05	2,34	2,77	2,35	2,42

Panel B: Equally Weighted Portfolio returns sorting by YoY earnings

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Excess Returns	1,63	5,50	5,50	8,78	9,84	10,71	9,05
T-Stat	0,33	1,13	1,31	2,12	2,35	2,64	5,04

6.4 Capital Structure Factor- Debt-to-Equity and Operating Cash Flow to debt

The findings on the relationship between capital structure and returns are mixed.

Modigliani and Miller, in their capital structure theory, stated that, in an efficient market, the value of a firm is not affected by the amount of debt and by how the firm is financed. In the second proposition of the theorem, they state that, in case of taxes, the value of the company will increase as it takes more debt, increasing the value of tax value. The theorem dates back to 60s and it lost the explaining power because it is not considered fully realistic. There is a trade-off theory when the concept of bankruptcy cost is introduced. The trade-off is between taking more debt and the risk of default. It should be considered the financial distress at the moment when the interest tax shield cannot be applied and the debt can have a negative impact.

Booth et al. (2001) and Fama and French (2002) found a negative relationship between the debt and the profitability, rejecting the trade-off theory.

Ghosh et al. (2000), Fernandez (2001), Hovakimian (2001), and Hadlock and James (2002) confirmed a positive relationship between profitability and capital structure, supporting the trade-off theory.

This ratio is included in quality definition by MSCI quality index and for this reason I'm going to analyse the relation with the returns.

6.4.1 Debt-to-equity and Stock Returns

As can be seen in Table 5, there is the investigation of the cross-sectional relation between Debt-to-Equity and expected returns with univariate sort portfolio analyses.

The results indicate a negative relation between them. The return on average is -4,27% (t-statistics is 1,98) per year and -2,97% (t-statistics of 2,01). Different weighting scheme produce quite same results that differs only in magnitude. With a Cap-Weighted Portfolios, the results are even stronger and statistically significant. The returns of the different portfolios are decreasing and consistent with the analysis. Because of this, I decide to include this ratio in the definition of Quality.

TABLE 5 Univariate portfolio analysis

This table presents the results of univariate portfolio analysis of the relation between Debt-to-Equity and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using Debt-to-Equity decile breakpoints calculated using all stocks in the sample. **Panel A** shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. **Panel B** presents the results for equally weighted portfolios. The analysis is carried out using the same breakpoints and the same decile as of cap- weighted. The numbers are in percentage.

Panel A: Value Weighted Portfolio Returns sorting by Debt-to-Equity

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	8,41	7,45	8,77	6,86	4,96	4,15	-4,27
T-stat	2,95	2,27	2,85	2,24	1,72	1,29	1,98

Panel B :Equally Weighted Portfolio Returns sorting by Debt-to-Equity

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	8,93	8,42	9,24	8,64	7,06	5,99	-2,97
T-stat	3,12	2,97	3,17	2,93	2,54	1,78	2,01

6.4.2 Operating Cash Flow-to-Debt and Stock Returns

In the following table 6, there is the relation between operating cash flow to debt and expected returns. This coverage ratio tells you how much a company can pay off its debt using the cash flow generated and thus whether it is able to carry more debt.

Panel A and Panel B show results that are robust and highly positive with average returns per year respectively of 5,74% (t-stat of 2,19) and 5,85% with t-stat of 2,57. This demonstrates that on average companies with higher ratio earn a premium, an excess return.

TABLE 6 Univariate portfolio analysis

This table presents the results of univariate portfolio analysis of the relation between Operating Cash Flow-to-Debt and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using Operating Cash Flow-to-Debt decile breakpoints calculated using all stocks in the sample. **Panel A** shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. **Panel B** presents the results for equally weighted portfolios. The analysis is carried out using the same breakpoints and the same decile as of cap- weighted. The numbers are in percentage.

Panel A: Value Weighted Portfolios sorting by Operating Cash flow-to-debt

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	4,50	2,65	3,61	5,97	6,97	10,23	5,74
T-Stat	1,38	0,98	1,55	2,65	3,42	2,88	2,19

Panel B: Equally Weighted Portfolios sorting by Operating Cash flow-to-debt

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	3,79	5,30	6,30	8,22	9,54	9,65	5,85
T-Stat	0,69	1,13	1,49	2,03	2,28	2,31	2,57

6.5 Earnings Quality Factor- Accruals component

One of the most used proxy for the earnings quality are the accruals, the adjustments to be made before financial statements are issued. Thus, the focus on the bottom line of the income statement provides a wrong view about the quality of the earnings.

For this reason, the literature extensively looked for a relationship between accruals and expected stock returns. As I said in the previous section, Sloan in 1996 was one of the first to find a positive relationship between low level of accruals and abnormal return. Those companies which are less manipulated and thus have low level of accruals earn higher return than those with high level of accruals. The papers cover data from 1962 to 1991 on NYSE and AMEX.

Another paper shows that accruals are negatively correlated with future stock returns[23]. Conversely, earnings growth connected with high levels of accruals are associated with lower future returns.

23 K. Chan, L. Chan, N.Jegadeesh and J. Lakonishok, 'Earnings Quality and Stock Returns', 2001

On the other side, Ray Ball, Joseph Gerakos , Juhani T. Linnainmaa and Valeri Nikolaev [24]demonstrated that cash-based operating profitability measures, which exclude accruals, outperform other measures of profitability which include accruals.

6.5.1 Accruals Component and Future Stock Returns

To understand this divergence in literature, I performed the analysis with the accruals as independent variable. I used a measure of accruals directly by downloading from Eikon API a function (EQ Accruals Component) that gives a score to each company from 1 to 100 based on the level of accruals. This measure is part of the Earnings Quality Score made by Refinitiv Eikon.
I adopted this indicator because of the missing data to avoid data mining bias.

The results are in the following Table 7. I could not find a statistically significant relation between accruals and excess returns in both the two specifications. The bottom portfolio is the one with the lowest level of accruals while the top portfolio is the one with the highest level of accruals. Thus, I expected a negative number in the long-short (top-bottom) portfolio to establish the negative relation.

In panel A, in the cap weighting scheme, the average excess return is only 0,28% with a t-statistics of 1,16. It's a very low difference in return and additionally is insignificant.

In panel B, the equally weighted scheme, the long-short portfolio gives a negative relationship between the highest accruals portfolio and future excess returns. The result is -1,09% but it is still insignificant with a t-statistics of only 1,21.

In conclusion, I didn't include an accruals component in the Quality specification because it was not statistically significant and not robust in my analysis.

TABLE 7 Univariate portfolio analysis

This table presents the results of univariate portfolio analysis of the relation between Accruals and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using Accruals decile breakpoints calculated using all stocks in the sample. **Panel A** shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. **Panel B** presents the results for equally weighted portfolios. The

[24] Ray Ball, Joseph Gerakos , Juhani T. Linnainmaa and Valeri Nikolaev, 'Accruals, cash flows, and operating profitability in the cross section of stock returns',2015

analysis is carried out using the same breakpoints and the same decile as of cap- weighted. The numbers are in percentage.

Panel A: Value Weighted Portfolios sorting by Accruals

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	9,01	8,29	2,86	6,15	7,84	9,29	0,28
T-Stat	3,32	3,39	1,15	2,28	2,17	2,55	1,16

Panel B: Equally Weighted Portfolios sorting by Accruals

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	10,35	9,14	6,14	7,16	8,17	9,26	-1,09
T-Stat	2,65	2,70	1,82	1,88	2,08	2,02	1,21

7. DATASET

The data set was constructed based on the Stoxx EU 600 index. The choice of this dataset was optimal for the analysis, although larger indices can also be similarly exploited, to increase the research base.

The main advantages of our sample index are:

- Highly efficient
- Highly liquid
- Historical data are plentiful and reasonably accurate
- Very scalable due to market capitalizations

Using Refinitiv Eikon as a source of data, I processed the data set in multiple steps. In order to develop a proper back-test in the past years, I retrieved the index constituents for every year, using a function of Eikon API.

The data are downloaded on yearly basis, starting from June 1999 to June 2021, as I started to invest in June 1999.

8. METHODOLOGY

In order to be consistent with empirical asset pricing, I made a series of hypothesis and test to identify a list of potential factors to elaborate a ranking based on the quality factor. I've taken into consideration 5 fundamental indicators to build this quality indicator. The macro-categories are profitability, earnings quality, capital structure and accounting quality.

The indicators are presented in Figure 1 and are Gross Profitability-to-Assets, ROA (Profitability factor), YoY Earnings Variability (Earnings Stability), and Debt-to-Equity, Operating Cash Flow-to-debt (Capital Structure).

Then I build a multi-factor portfolio through a simple methodology. It is performed using this approach:

1. I calculate the sector median for each variable.
2. I compare each company with the sector median of its interest.
3. I assign a different score based on the threshold it reaches.
4. I elaborate a final ranking consisting of the best 10% and the worst 10%.

9. SCORING SYSTEM

The scoring system is as follows (see Figure 1): for each of the 5 variables from 3 different macro-categories, I assign a score of 1 if it is excess by at least 50% the industry median, a score of 0.5 if it is above 20% and below 50% from the industry median.

Then I assign a negative of -1 if it is 50% lower than the industry median and only -0.5 if it is lower than 20% from it.

All of the variables are assigned with equal weights, 20% per each variable, for the construction of the combined rank.

For Debt-to-Equity and the standard deviation Year over Year Earnings, the logic used is the inverse, giving a negative score to the one that is higher than the peers and a positive score to the other that is lower than the peers.

Thus, I have defined quality as a combination of signals from different categories.

Figure 1

Reference Variables and Rules - Score Point Grading System	**WEIGHTS: ---------->**	
Profitability	Rules	Scorepoint
Gross Profit-to-Total Assets	Higher than 50% from peers	1
Return on Assets	Higher than 20% from peers	0,5
Capital Structure	Lower than 20% from peers	-0,5
Operating Cash Flow-to-Debt	Lower than 50% from peers	-1
Debt-toEquity		
Earnings Stability		
YoY Earnings Variability		

10. PORTFOLIO CONSTRUCTION

The entire thesis is based on Refinitiv Eikon data provider from which all data were taken. The Stoxx Europe 600 index is the universe.

I determined that the portfolio should be rebalanced every year in July, the month in which company data are released and are readily available. All companies for which I had no data were removed from the portfolio construction. The first portfolio was constructed in July 1999, the last in July 2020, so that annual returns could be calculated from July 2020 to July 2021.

After scoring, as stated in the scoring system section, the scores for each variable with equal weight are combined to create a combined ranking. At this point I select the top 10% and the bottom 10%. The best 10% will be the companies in which I'll have a long position, while the worst 10% are the companies in which I short sell (a short position). I combined the long and short position, in order to exploit the quality factor and to create a portfolio that is balanced to take advantage of both rises and falls in the market. This limits the downside risk and the maximum drawdown.

10.1 Calculating Returns

The returns of the portfolio and for the companies are calculated as follows:

$$Percentage\ Return = \frac{P(t+1) - P(t)}{P(t)}$$

Where:

- P(t+1) is the price at time t+1, the following year since a stock is purchased
- P(t) is the price at time t, the year the stock it was purchased

As can be seen, the dividends are excluded for simplicity and because sometimes are not available.

After calculating individual stock returns, they are weighted with the relative size. The weighting scheme used are two: a value-weighted and an equally weighted. Then, the relative weight is multiplied by the stock return, and they are summed up. This gives the annual portfolio return.

$$Rp = \sum_{i} w_{P,i}\, R_i$$

In the first weighting scheme, the weights are determined with the total number of shares multiplied by the current market price.

$$Weight\ (market\ Cap\ weighted) = \frac{Number\ of\ shares \times Stock\ Price\ (i)}{Total\ sum\ market\ Cap}$$

Where:

- the total sum market cup is the sum of the market capitalization of each company
- Number of shares is the number of shares outstanding of a company ***i***
- The stock price of a company ***i*** is the current market price
- The multiplication between them is the market capitalization of a company

An equally weighted scheme assigns equal weight to each company in the portfolio.

$$Weight(\ equally\ weighted) = \sum_{i=1}^{n} (\frac{Return(i)}{n})$$

Then an annual average return and compounded return are calculated as well as for an annualized standard deviation.

Each portfolio performance is benchmarked against MSCI Europe Index, Stoxx EU 600 and MSCI Quality Index.

10.2 Performance Measures

10.2.1 Sharpe Ratio

Unfortunately, many investors rely only on return without considering fundamental parameters for a 360-degree analysis. The best portfolio is the one that achieve the highest return at the lowest risk. However, this type of portfolio is a utopia and is difficult to create in practice as even active successful managers can hardly beat the market.

One of the most widely used measures of risk adjusted return is the Sharpe ratio, proposed by Bill Sharpe. The Sharpe ratio is defined as:

$$SR = \frac{R_p - R_f}{SD}$$

Where:

- R_p is the return of a given portfolio p
- R_f is the risk free rate
- SD is the standard deviation of the portfolio

The Sharpe ratio evaluates the portfolio of a manager considering both return and diversification.

10.2.2 Jensen's Alpha

The Jensen measure is calculated using CAPM formula. It was proposed in 1968 by Michael C. Jensen and tells you the excess return of the portfolio over the expected return, given by the CAPM.

Formula 1

$$Jensen's\ Alpha = R_p - (R_f + \beta_a [E(R_m - R_f)])$$

A positive alpha means that a portfolio manager delivers an average return above the one predicted by the CAPM. The purpose of this formula is to determine whether a manager consistently beats the market.

The alpha can be the CAPM alpha or the Fama and French 3-factor alpha. The former is the one above in Formula 1. The latter can be described as follows:

$$FF\ 3-factor\ Alpha = R_p - (R_f + \beta_{i1} MKT + \beta_{i2} SMB + \beta_{i3} HML)$$

Where:

- MKT is the market factor, the expected excess return of the market
- SMB is Small Minus Big and is the size factor
- HML is High Minus Low and is the value factor

The alpha, calculated as above, allows to control for other additional factors that historically earned a premium. In this way, the size and value anomalies can be corrected by this formulation

10.2.3 Information Ratio (IR)

Information Ratio (IR) is an indicator calculated as the ratio between the portfolio's excess return compared to the benchmark index and the Tracking Error Volatility, i.e. the volatility of the portfolio's differential returns compared to the benchmark index. In other words, it's the Jensen's alpha scaled by the residual risk or the standard deviation of the error term in the CAPM regression.

$$IR = \frac{\alpha_p}{\sigma(\varepsilon_p)}$$

Where:

- α_p is the Jensen's alpha of the portfolio
- $\sigma(\varepsilon_p)$ is the tracking error or the standard deviation of the error term in CAPM equation

10.2.4 Tracking Error (TE)

A useful tool to compare the performance relative to a benchmark is the Tracking Error, a way to measure the active risk. It is used for reporting and performance analysis. It is usually expressed in annualized terms.

$$Tracking\ Error(TE) = \sigma_{R_a} = \sigma_{(R_P - R_{b)}}$$

Where:

- σ_{R_a} is the standard deviation of the active return, i.e. the standard deviation of the return of the portfolio minus the return of the benchmark.
- $(R_P - R_{b)}$ is the return of the portfolio minus the return of the benchmark.

The tracking error will be higher when:

- the portfolio's beta differs from 1 (lower or higher)
- The market volatility is high
- The portfolio si very concentrated
- The stocks of the portfolio are not included in the benchmark

It gives you an immediate idea of what kind of portfolio it is. A passive indexing portfolio has a tracking error below 1%, a semi-passive indexing between 1% and 4% and an active portfolio is above 4%.

10.2.5 Maximum Drawdown (MDD)

When you analyse the performance, you should consider the portfolio that suffers less during market downturns because a major loss can generate dissatisfaction and thus a disinvestment.

It is a measure of the investor's risk and can be thought of as the maximum loss he could incur by buying at the highest level or selling at the lowest.

$$MDD = \frac{P - L}{P}$$

Where:

- P is the peak value before largest drop
- L is the lowest value before new high is achieved

10.2.6 Calmar Ratio

This is an important statistical indicator used to measure the average return in relation to the drawdown risk: it allows the investor to compare the potential gain and the possibility of loss of a given investment. It is created by Terry W. Young and first appeared in Futures (1991).

$$Calmar\ Ratio\ = \frac{Average\ Annual\ Return}{Maximum\ Drawdown}$$

It tells you the efficiency of an investment on a risk-adjusted basis. A low ratio indicates that the drawdown was great and high ratio means that the performance has not been affected by such huge negative impacts.

11. RESULTS- LONG ONLY AND LONG SHORT STRATEGY

In the following section, I will present the key results of the portfolio, how it could be integrated with previous studies, as well as the limitations of this research.

Since I also would like to put in the retail investor's point of view, the first section is dedicated to the long-only portfolio because it is simpler to construct, and you don't have any liquidity or leverage constraints.

Analysing the results and comparing the various weighting schemes to the benchmarks, I can say undoubtedly that there is an outperformance against any indices and that the best is the Cap weighted portfolio, one of the simplest weighting schemes, achieving the best risk-adjusted performance.

In active management, the choice of the benchmark is extremely important as active managers are remunerated when they outperform it. The positive alpha and the excess return they seek to generate means a higher fees for them. A successful active manager can ask for higher fees due to his achievements. I have selected the Stoxx Europe 600, i.e. the universe from which I pick the stocks, MSCI Europe index, which covers approximately the 85% of the market capitalization across European developed Markets equity universe.

In the second section, it will be presented the Long-Short construction, which is aimed at improving the factor exposures and to see whether the quality factor is consistent.

We will see that this market neutral strategy works better with the equally weighted scheme, compared to the cap weighted. Otherwise, I used a long-short equity index as a benchmark and the performance is not so attractive as the Long-Only strategy.

11.1 Long-Only Portfolio

As you can see in Chart 1, the relationship between the four portfolios is clearly visible and immediate. The chart shows the cumulative performance of the long-only style portfolios against the two benchmarks considered. Here, the cumulative returns are calculated without taking into consideration taxes and fees as well as turnover for simplicity.

The cumulative performance for the equally weighted portfolio (P-EW) is 178% and for the cap weighted (P-CW) 155%. The two portfolios appear to outperform the benchmarks throughout the period, although until 2007 MSCI Europe did extremely well. After the Subprime Mortgage Crisis, the European Markets were also affected by the crisis and the MSCI index suffered (the maximum drawdown is 103,48%). The financial crisis is a is a crucial point for observing the graphs and provides a starting point for several observations that will be seen in detail in the following section.

P-CW and P-EW also were compromised by the financial crisis, but they reacted well with a strong rebound after that. They follow an almost identical trend, the blue and orange line, but the P-EW has stronger effects in magnitude.

The average annual excess returns are 7,60% for the P-EW, 8,39% for the P-CW, 0.82% for the stoxx EU and 1.74% for the MSCI index. Based purely on excess returns, the best is the cap-weighted portfolio, with an outperformance of 8,39%.

On risk-adjusted returns, the top performer is the Cap Weighted portfolio with a surprisingly Sharpe Ratio of 0,66. The Cap-Weighted portfolio is able to generate the most profit, in adjusted-return terms. This is mainly related to the strong expansion, in terms of capitalization, that the market has undergone in the previous decade.

It has the highest Sharpe Ratio identified, with the best average annual return of 8,73% and a relatively low standard deviation of 13,23%. In this way, the portfolio is able to grow steadily, at a relatively low-risk rate. In addition, the maximum DrawDown of 48,24% is also very significantly low. This value shows how well the portfolio reacts during turbulent market periods and how it outperforms other portfolios.

On the other portfolios, the Sharpe Ratio for the P-EW is 0,63, while for the benchmark is only 0,04 and 0,08. This difference is also due to the very high volatility of the two indices with an average 20% of annualized standard deviation.

Positive days and months are calculated because, from the investor's point of view, they are critical, as he might disinvest if dissatisfied. In behavioural finance, a study from Journal Economics shows how investor mood and feeling changes affect equilibrium stock returns[25]. The sentiment of an investor is one of the arguments against the efficient market hypothesis, as the individual might react irrational. As can be seen in Table 7, the positive days and months are quite stable across the different portfolios with an average 52% for the days in which the portfolio gained and 55% for the months in which the portfolio was in profit. The peak of 66% for the positive months is from the Cap-Weighted portfolio.

The lowest maximum DrawDown is 48,24% (P-CW), and it gives an idea of the positive management during downturns, which gives a competitive advantage when markets later recover. On the other side, the worst is the MSCI Europe (103,48%), during the Financial Crisis of 2007 and 2008. The P-EW has a maximum DrawDown of 60,59%, which is not low, meaning that the portfolio didn’t react so positively during market turbulence of 2007-2008

The highest Calmar Ratio is of P-CW (18,09%), as it is the best portfolio on a risk-adjusted basis during the given timeframe, while the benchmarks have a very low Calmar Ratio of 0,87% for Stoxx EU 600 and 1,68% for MSCI Europe.

In conclusion, I can say that the Long-Only Cap-Weighted Portfolio outperformed in every aspect, in terms of both risk and returns. The strong ability to bounce back after the period of severe crisis, not only in 2007-2008 but also during Covid Crisis, makes it an attractive portfolio from an investor's point of view.

[25] Hui-Chu Shu, ‘Investor Mood and Financial Markets’, 2010

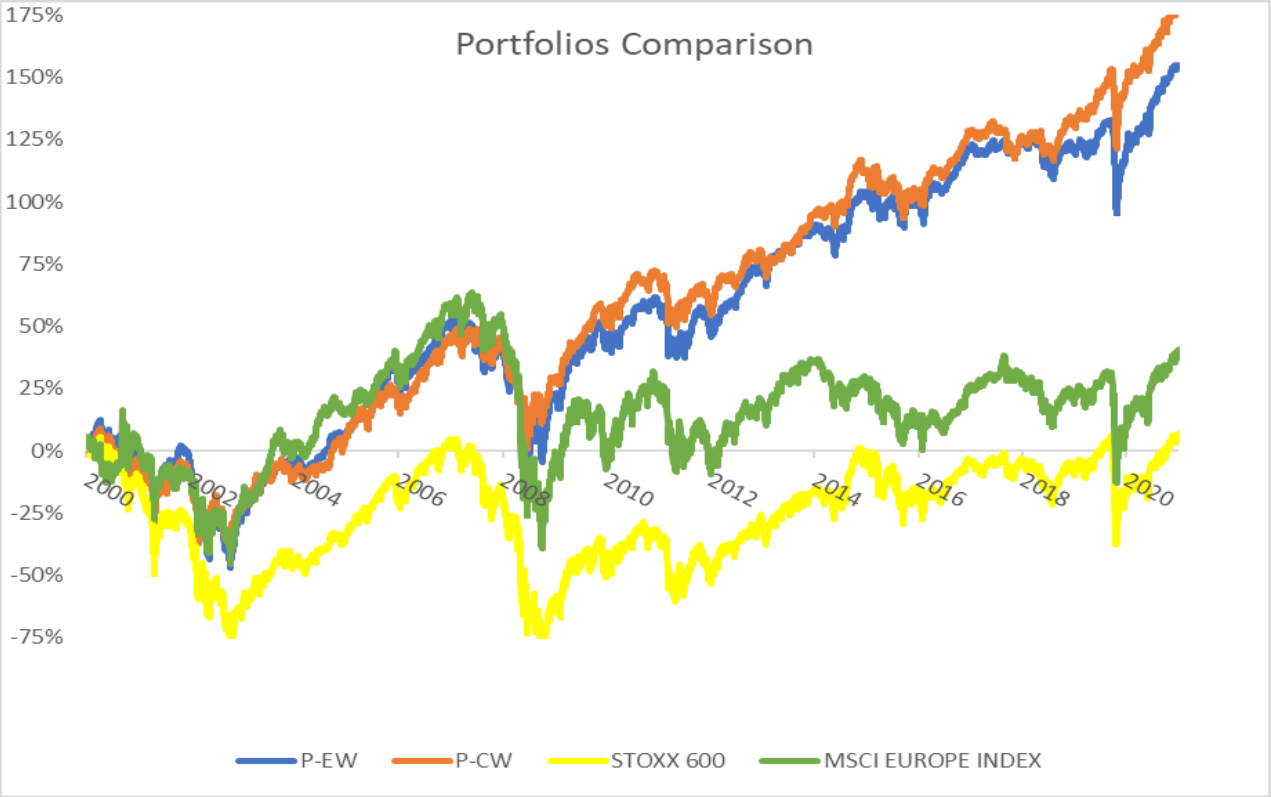
I can conclude this section by saying that one of the characteristics of the quality factor is already clear, which is that the Quality Factor does extraordinarily well in times of crisis and recovers immediately afterwards. It is similar to the low volatiity factor with stronger effects in terms of returns. Later, I'll present the correlation with different factors, analysing the similarity and the difference.

TABLE 8 Performance Comparison

In this table are presented the results of 4 different portfolios. The analysis covers from June 2000 to June 2021. The average excess return is calculated by averaging the years taken into account, once all the annual returns have been aggregated minus the risk-free rate. The standard deviation is annualized multiplying by the daily standard deviation with the square root of 260. The sharpe ratio is the ratio between average annual excess return and the standard deviation. The positive days are calculated with SUMIF excel function as well as positive months. The formula for the maximum drawdown (Max DD) is: $D(T) = max\{0, max\, X(t) - X(T)\}\ \ where\ t \in (0, t).$ The calmar ratio is the ratio between average excess return and the absolute value of the maximum drawdown. These indicators are explained in the early section.

	P-EW	P-CW	STOXX 600	MSCI EUROPE INDEX
Average Annual Return	7,60%	8,73%	0,82%	1,74%
Standard Deviation	12,13%	13,23%	19,56%	22,52%
Sharpe Ratio	0,63	0,66	0,04	0,08
Positive Days	54,93%	54,43%	52,23%	52,50%
Positive Months	53,85%	66,01%	56,13%	54,15%
Max DD	60,59%	48,24%	93,97%	103,48%
Calmar Ratio	12,54%	18,09%	0,87%	1,68%

CHART 1



11.1.1 Compound return

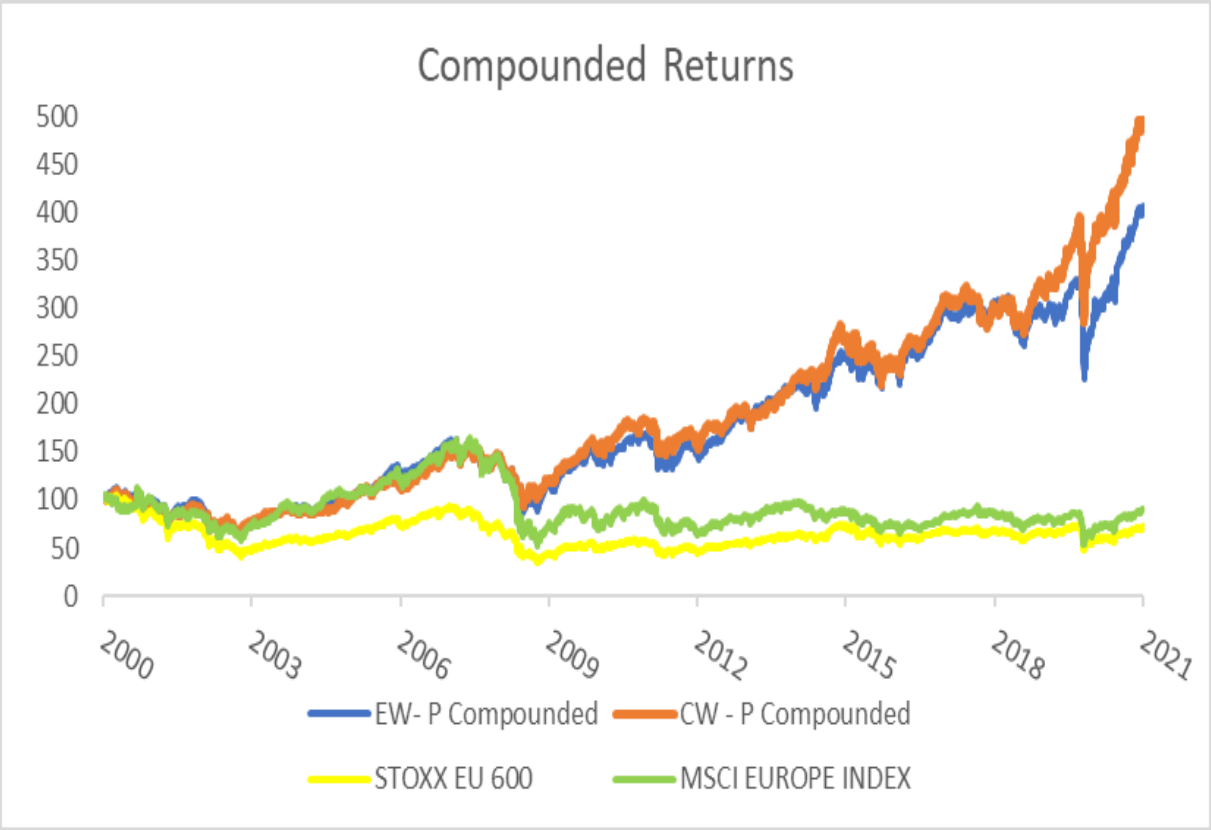
The average annual return doesn't consider the compounding effect over time. It represents the cumulative effect that a series of gains or losses has on an original amount of capital over a period. Since the dividends are not calculated in this thesis, I'd like to do a job as accurate as possible, and it seemed to make sense that the gain from a dividend or any interest would be reinvested in the portfolio.

I would like to see if I had invested $100 how it would grow 20 years later considering the compounding effect. A one hundred dollars invested in the S&P 500 in January 1984 would have been worth $3800. The S&P 500 is a market capitalization weighted index of the 500 largest U.S. companies with an average annual return of 10%. I don't want to compare the two markets, but this gives an idea of the extraordinary effect of compounding over time. A greater performance, in terms of compound return is achieved by Warren Buffett in Berkshire Hathaway. This surprisingly performance is partly due to the higher volatility than the market volatility. The strategy of Buffett is to buy the right stocks at the good price, based on the Graham and Dodd principles. During downturns, he stood firm on his principles, he didn't retreat or rethink about the strategy and this was one of the secrets of this manager. In this sense, a manager's skill lies in his ability to generate

returns over time and to stick to his principles, because the market turbulences are cyclical and present in every moment.

If you had invested $100 in the Quality sort portfolios in June 2000 would have been worth in June 2021 $500, which is quite good considering the European market and the financial crisis of 2007-2008. Compared to the MSCI Quality Europe index, the P-CW outperformed against it.

CHART 2



11.1.2 Cap-Weighted Long-only Portfolio

11.1.2.1 Performance, year-by-year

Table 8 shows the annual performance, decomposing risk and return year by year. This table visually emphasis the best periods, which are in green, and the worst periods in red.

The portfolio is constructed and coincides with the Dotcom Bubble, making heavy losses for the first three years, but still small compared to other benchmarks, reaching -13.42% with an annual volatility of 21,82%. The Financial Crisis of 2007-2008 made the portfolio less attractive with a loss of -32,59% and a volatility of 21,62%, respectively the lowest return and the highest standard

deviation. After this, the portfolio rebounded back with an annual return of 32,53% and a standard deviation of 10,94%.

Despite the four major crises of the past twenty years, the portfolio seems to react well, and the performance is good. One of the characteristics that makes this portfolio attractive is its ability to minimise losses relative to other factors, such as size, value and momentum (this feature will be discussed in the next section).

TABLE 9

ANNUAL PERFORMANCE (%)		
Year	Long Portfolio	
	Annual return	Annual volatility
2000	-2,71%	9,27%
2001	-8,79%	15,72%
2002	-13,42%	21,82%
2003	14,92%	15,97%
2004	4,00%	8,86%
2005	27,23%	11,98%
2006	13,25%	11,36%
2007	13,37%	10,15%
2008	-32,59%	21,62%
2009	32,53%	10,94%
2010	23,36%	12,66%
2011	-11,97%	16,75%
2012	11,68%	10,02%
2013	11,93%	13,43%
2014	16,71%	8,45%
2015	5,16%	14,15%
2016	9,57%	10,26%
2017	13,94%	7,05%
2018	-10,82%	12,19%
2019	29,78%	7,86%
2020	16,10%	21,60%
2021	15,11%	7,57%

11.1.3 Equal-Weighted Long-only Portfolio

11.1.3.1 Performance, year by year

As I show you in the early section, Table 9 aims to visually identify the characteristics of the equally weighted portfolio, emphasising the positive and negative periods with green and red colours respectively.

In this way, periods can be compared year by year with the cap weighted portfolio. It can be already seen that in the first 3 years, in the middle of the dotcom bubble, performance is severely negative, with a return of -25,39% in 2002 and an annual volatility of 25,15%. The effects of the Dotcom Bubble are stronger in magnitude in the Equally Weighted portfolio as well as the recovery in the year after with a +21,11% and a standard deviation of 16,41, realizing a surprising Sharpe ratio of 1,21.

During the Financial Crisis, the situation doesn't change, and the losses of the portfolio are huge (-35,79%). The Equally Weighted portfolio had severe losses at the worst times but also extraordinary gains. The riskiness is higher but not well remunerated compared to the other Cap Weighted portfolio, which therefore becomes preferable for investors.

TABLE 10

ANNUAL PERFORMANCE (%)		
Year	Long-Only Equally Weighted	
	Annual return	Annual volatility
2000	2,26%	9,91%
2001	-8,25%	21,66%
2002	-25,39%	25,15%
2003	21,11%	16,41%
2004	9,76%	7,69%
2005	21,45%	9,85%
2006	18,81%	9,82%
2007	3,51%	12,62%
2008	-35,79%	25,16%
2009	34,96%	17,98%
2010	15,60%	15,56%
2011	-13,92%	18,26%
2012	20,32%	11,80%
2013	18,08%	13,82%
2014	7,79%	10,26%
2015	7,42%	12,69%
2016	10,30%	8,12%
2017	14,89%	6,26%
2018	-13,14%	13,18%
2019	21,85%	11,17%
2020	9,90%	32,65%
2021	13,68%	5,98%

11.1.4 Which Types of Stocks? Fama French 5-factor Model

We do not yet know what characteristics the stocks I have selected have in terms of risk premium factors. To address this question, I considered the factor exposures of the portfolio with the results of the Fama and French 5-factor model.

This 5-factor model was developed by Eugene Fama and Kenneth French to describe stock returns. The old model was the 3-factor, which consists of market risk, size and value. The size effect is that stocks with small capitalization outperforms on average the stocks with big capitalization. The value effect is that cheap companies with a low price to book earn higher returns on average than expensive companies with a high price to book. The two Nobel laureate Fama and French proposed two additional factors:

- Profitability Factor
- Investment Factor

The first describes the excess return that companies with high operating profitability have earned with the respect to the company with low operating profitability. The latter notes that stocks with high total asset growth underperform the stock with low level of growth. This factor is related to the high expectations that investors have for those companies that makes high investments.

Both new factors are examples of what can be called quality factor. In a paper from Robeco, the authors criticise the timing for this addition because they are recently discovered factors. Moreover, Hanauer says that a different definition for quality would have been more appropriate, such as the definition given by Robert Novy-Marx with the gross profitability factor. Other opinion is that Momentum and low volatility are not included in the model, although they are factors well accepted in academia for 20 years.

Despite the arguments against it, this model is still valid and used by academics to consider the factor loadings. The model is as follows:

$$R_t - R_t^f = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t$$

Where:

- $R_t - R_t^f$ is the excess return over the risk free rate at time t
- MKT is the excess return of the overall equity market

- SMB is the size factor (small minus big)
- HML is the value factor (high minus low)
- RMW is the profitability factor (robust minus weak)
- CMA is the investment factor (conservative minus aggressive)
- The beta coefficients tell you the factors' exposures, how much the portfolio is exposed to a given factor or the sensitivity of the portfolio to the changes in those variables.

11.1.5 Factor Loadings- Fama French

11.1.5.1 Cap-weighted Long-Only portfolio

In this section, as shown in Table 10, I ran this regression for the excess return of the Cap-Weighted long-only portfolio. The data are downloaded from Kenneth R. French website for the European 5-factor monthly returns.

I first ran a regression on the market return. The portfolio has a beta of 0,53, less than 1, statistically significant at 5% level, meaning that the portfolio is less volatile than the market portfolio. Next, I ran multiple regressions in order to control for the standard factors I explained early.

The size factor is not statistically significant, while the value factor is significant at 5% level. It has a negative value that ranges from -0,24 to -0,26, which shows the propensity of this portfolio to buy expensive companies, although value indicators, such as price-to-earnings or dividend yield, are not included. Quality sometimes is referred to expensive companies and, in this cap-weighted portfolio seems to have this inclination.

Moreover, the portfolio has an insignificant loading on RMW, the profitability factor, a prominent factor in quality definition. The positive loading on CMA, the investment factor, reflects the tendency to buy companies with low level of investments.

The alphas are annualized and are monotonically increasing. As it can be seen, these five factors don't explain so much of the alpha shown in Table 10. The alpha is 5,36% for the 5th regressions. This alpha generated by the portfolio could be driven by other factors such as the Momentum Factor (UMD, up minus down) as well as the low-volatility factor (BAB, betting against beta) or the quality factor (QMJ, quality minus junk). In the European context, we don't have much data to analyse it.

TABLE 11

Cap Weighted Portfolio, 6/2000-5/2021 (t-statistic in parentheses)						
Alpha*	**3,84**	**3,81**	**4,57**	**5,31**	**5,36**	
	(1,72)	(2,51)	(2,07)	(1,71)	(2,29)	
Mkt-RF	**0,53**	**0,53**	**0,56**	**0,55**	**0,54**	
	(15,52)	(15,15)	(15,83)	(14,7)	(12,01)	
SMB		0,0134	0,0021	0,0006	-0,0040	
		(1,47)	(1,23)	(1,01)	(0,77)	
HML			**-0,24336**	**-0,28038**	**-0,26082**	
			(-3,48)	(3,53)	-2,48	
RMW				-0,13477	-0,13159	
				(0,91)	-0,96	
CMA					**0,040359**	
					(1,90)	
R Square	0,70	0,71	0,71	0,71	0,71	
Obs.	252	252	252	252	252	
*Alphas are annualized. Boldface indicates statistical significance at the 5% level						

As shown in Table 12, the results of a regression of the daily returns of the portfolio on the daily returns of the European Fama French 5 factor model are summarised.

Since the days on the calendar between Fama French data and my sample did not match, I had to use the index match excel function to find those dates for which I had the returns of both samples. Some calendar days are excluded for this reason. The regression is done with regression from data analysis tool in Excel. The number of observations is 2888 days. The R squared is low (0,22) but in this type of regression is considered normal, because of collinearity.

The market factor is low reflecting the tendency to buy low volatile stocks with the respect to the market. The coefficient is only 0,289 with a t-statistics of 2,905.

The size factor is slightly negative, meaning that the portfolio prefers stocks with big market capitalization. this reveals a feature of the quality factor: the tendency to buy large, safer, and less volatile stocks. The t-statistics is 3,684 and is statistically significant at 5% level with a very low p-value.

The value factor (HML) is negative, as the previous regression. The significant loading (with a t-statistics of 3,9) of -0,114 means that the selection doesn't consider the value argument, picking stocks with low price to book.

The profitability factor, as opposed to the other regression, is statistically significant at 5% and is largely positive. The loading on RMW is 0,246 with a p-value tending to 0, indicating the tendency to buy high profitability stocks while flying away from low profitability stocks.

The investment factor is consistent with the previous regression, but even stronger in magnitude. The loading on CMA is 0,161 with a t-statistics of 4,11, revealing that the stocks included in the portfolio are safer and conservative with low level of investments.

The alpha generated by the portfolio, using daily data, is positive (3,15%) and is significant.

TABLE 12

SUMMARY OUTPUT	
Regression Statistics	
R Square	0,227
Adjusted R Square	0,226
Observations	5288

Factors	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Alpha *	**3,150**	0,011	2,905	0,004
Mkt-RF	**0,289**	0,013	6,886	0,000
SMB	**-0,090**	0,024	3,684	0,000
HML	**-0,114**	0,029	-3,913	0,000
RMW	**0,246**	0,042	-5,900	0,000
CMA	**0,161**	0,039	-4,117	0,000

* Alpha is annualized

11.1.5.1 Equally Weighted Long-Only portfolio

in this section, the same procedure as above will be repeated with the equally weighted portfolio. The data were previously downloaded from the Kenneth website. R. French.

As shown in Table 12, I ran multiple regression sequentially for the excess return, $R_t - R_t^f$, of the equally weighted long-only portfolio.

The first regression is the CAPM with only the market factor. The beta, associated with this factor, is higher than the cap-weighted (0,69 instead of 0,55), meaning that this portfolio is more cyclical and sensitive to the market movement. It is given higher weights to those stocks in Hi-Tech, automotive and airline sector. It is highly significant with a t-statistics of 19,69 and the given alpha is 1,75% on annual basis (with a t-stat of 2,72).

After controlling for the size factor (SMB), the market beta remains constant while the alpha is decreased. This means that the performance of the portfolio can be explained by the size factor. In fact, the coefficient is 0,25 (with a t-stat of 2,67) and highly significant. This reflects the tendency to buy stocks with small market capitalization, as opposed to the commonly accepted definition of quality, for which the stocks with a large market capitalization are safer.

In many indices of quality, the size factor is negative because the larger companies are less risky than smaller companies and it is included in the definition by academics. This difference can be explained by the fact that this is a long only strategy and it's aimed only to produce an abnormal return, as opposed to the market-neutral strategy aimed at creating a factor.

TABLE 13

Equally Weighted Portfolio, 6/2000-5/2021 (t-statistic in parentheses)						
Alpha*	**1,75**	**1,12**	**1,51**	3,21	3,41	
	(2,72)	(2,51)	(2,07)	(1,71)	(1,45)	
Mkt-RF	**0,69**	**0,69**	**0,71**	**0,68**	**0,66**	
	(19,69)	(19,95)	(19,76)	(18,15)	(15,24)	
SMB		**0,25**	**0,24**	**0,24**	**0,22**	
		(2,67)	(2,62)	(2,61)	(2,36)	
HML			-0,12	**-0,21**	-0,13	
			(1,74)	(2,61)	(1,22)	
RMW				**0,31**	**0,30**	
				(2,25)	(2,15)	
CMA					**-0,16**	
					-2,03	
R Square	0,77	0,77	0,78	0,79	0,79	
Obs.	252	252	252	252	252	
*Alphas are annualized. Boldface indicates statistical significance at the 5% level						

As the regression in the previous section, the value factor (HML) is negative but not statistically significant, with the exception of the 5th regression. This loading varies from -0,12 to -0,21 and indicates the tendency to buy more expensive companies than cheaper.

The significant loadings on the profitability factor (RMW) of 0,31 and 0,30 mean that the portfolio strives for high profitability stocks than low profitability ones. This is a huge difference which is not captured in the previous section. The t-statistics is 2,25 and 2,21 respectively, with a p-value close to zero.

As shown in Table 12, the loading on the investment factor (CMA) reveal the tendency for high investment stocks, as opposed to the low investment stocks. The growth stocks are riskier because they invest in many projects or products.

The t-statistics of the alpha is decreasing, meaning that the 5 factors cannot fully explain the performance, which must be explained by other factors. The alpha is smaller than the regression in the previous section, but it is still positive. The R squared is higher with an average of 0,78.

To be consistent with the econometry, I repeated this analysis using daily returns as a robustness check.

As can be seen in Table 13, I ran a regression of the daily returns of the portfolio on the daily returns of the Fama French 5 factor model.

The R squared is 0,72 with 5288 observations as the matched calendar days. I carried out the same procedure as illustrated before.

The alpha, generated by the portfolio, is positive (2,65%) on annual basis and statistically significant as well as for the cap-weighted portfolio, but weaker.

The market factor is low (0,28) but not statistically significant (1,22).

The size factor is consistent with the previous regression, it is positive (0,142) and highly significant (with a t-statistics of 4,35).

The value factor (HML) confirms the tendency of the portfolio to buy stocks with a low price-to-book and fly away from stocks with high price-to-book, even though cheaper stocks are a source of alpha generation. Sometimes, some stocks are so cheap for specific reasons such as low profitability, and the quality factor enables to distinguish this cheap but unprofitable companies from expensive but profitable ones.

The profitability factor (RMW) is positive and robust with the analysis, with a coefficient of 0,381 and a t-statistics of 3,40.

The investment factor is negative with a -0,197, reflecting the trend of the previous regression and statistically significant.

In conclusion, the alpha generated by these regression remains positive, ranging from 1,25% to 3,5% on an annual basis. The performance is not fully explained by these factors and should be analysed further with other factors taken into the model.

TABLE 14

SUMMARY OUTPUT	
Regression Statistics	
R Square	0,72
Adjusted R Squa	0,68
Standard Error	2,65
Observations	5288

Factors	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Alpha *	**2,649**	0,009	2,041	0,041
Mkt-RF	0,286	0,010	-1,222	0,222
SMB	**0,142**	0,020	-4,347	0,000
HML	**-0,137**	0,024	-1,968	0,385
RMW	**0,381**	0,034	3,406	0,001
CMA	**-0,197**	0,032	4,354	0,000

* Alpha is annualized

11.1.6 Comparison with MSCI Europe Quality index

To analyse the difference between the portfolio illustrated above and a quality index, designed by MSCI, I ran a regression on the returns of this index to the returns of the Fama French 5-factor model. In this regression, as can be seen in Table 14, the alpha is insignificant as the factors explained the composition of the portfolio. The market beta is 0,8 on average, meaning that the index is more volatile than the portfolio. Another feature is the size factor, which is negative and the opposite to the coefficient of the portfolio. The value factor is ambiguous, changing from negative to positive. The profitability factor is highly positive and significant. This factor explains part of the alpha generation. The investment factor is negative, but not statistically significant.

TABLE 15

MSCI Europe Quality Index, 6/2000-5/2021 (t-statistic in parentheses)						
Alpha*	2,70	3,20	1,66	1,56	1,11	
	(0,84)	(1,17)	(0,57)	(0,56)	(0,39)	
Mkt-RF	**0,82**	**0,80**	**0,79**	**0,78**	**0,78**	
	(11,17)	(11,05)	(12,42)	(11,27)	(9,94)	
SMB		-0,28	**-0,40**	**-0,31**	**-0,36**	
		(1,69)	(2,69)	(2,71)	(2,22)	
HML			**-0,30**	**0,01**	**0,10**	
			(3,38)	(3,23)	(2,88)	
RMW				**0,722541**	**0,722946**	
				(2,91)	(-2,71)	
CMA					-0,21853	
					-0,92	
R Square	0,82	0,84	0,86	0,88	0,89	
Obs.	252	252	252	252	252	
*Alphas are annualized. Boldface indicates statistical significance at the 5% level						

11.1.7 Tracking Error

As I told before, an active manager seeks to generate an alpha and to earn an abnormal return. As opposed to a passive strategy, an active strategy tries to outperform the benchmark or the index, picking different stock from them within certain risk boundaries. The tracking error, measuring the distance from the index or benchmark, should be higher, for definition, for the active portfolio.

In the Long-Only strategy, I expect a large tracking error since the construction of the portfolio differs enormously from the one of the indices I chose as benchmark, the MSCI Europe index, as well as for the Stoxx EU 600.

I also calculated the Tracking Error at Value at Risk, which is the worst expected TE at the 95th percentile.

Then, I annualized the Tracking Error because it is a measure that is generally expressed in annual terms.

The tracking error is similar in both portfolios, and it makes no difference whether you look at Stoxx Europe 600 or MSCI Europe as an index. It is a very large value, which means that the portfolio deviates a lot from the market portfolio.

We will have a situation where the portfolio is very concentrated, where the beta, as mentioned above, is much lower than 1, which makes the tracking error extremely high, as well as there are stocks not included in the benchmark compared to MSCI.

The annualized tracking error is 24%, if considered the MSCI Europe index, and it is 21,60%, if considered the Stoxx EU 600. I expected this incredibly number because the portfolio is constructed to earn an excess return and the aim was to deviate from the European market portfolios.

Despite these large values, the tracking error has some limitations because it fails to distinguish between various sources of alpha:

- Stock Picking
- Market or Factor Timing

For this reason, Cremers and Petajisto, in 2009, have proposed an alternative measure, called Active Share, which tells you the non-overlapping proportion of the portfolio with the respect to the benchmark. This formula allows you to distinguish between stock picking and market timing.

MSCI Europe	TE (daily)	TE At VaR*	TE (annualized)
Cap-Weighted	1,51%	2,5%	24,0%
Equally-Weighted	1,53%	2,5%	24,3%

*TE at Value at Risk is the extreme expected Te at 95th percentile

STOXX EU 600	TE (daily)	TE At VaR*	TE (annualized)
Cap-Weighted	1,361%	2,24%	21,60%
Equally-Weighted	1,358%	2,23%	21,55%

*TE at Value at Risk is the extreme expected Te at 95th percentile

11.1.8 Diversification Benefits

The benefits of a well-diversified portfolio can be incredibly high if stocks or strategies are not perfectly correlated with each other. Conversely, if they are perfectly correlated, diversification is zero. These benefits can translate into effective risk reduction and thus higher risk-based returns. Integration benefits increase when correlation between style or asset classes is low and increase when the tracking error is high[26].

[26] Shaun Fitzgibbons, Jacques Friedman, Lukasz Pomorski and Laura Serban, 'Long-Only Style Investing: Don't Just Mix, Integrate', The Journal of Investing , 2018

Fund managers often try to diversify across asset classes such as stocks, bonds, commodities and real estate. In this thesis, the diversification is simplified using a mix or an integration of strategies within a portfolio.

The difference in performances is larger when the combined styles are negative correlated or when more individual styles are being combined. I calculated the correlation between the portfolio return and the MSCI Europe Value index return. The results are quite surprising because the correlation is low but not negative as I expected.

Historically, combining value and quality has been a good strategy for their low correlation. From an investor perspective, the rationale behind is that value investors buy stocks that are cheap but low quality and quality investors buy stocks with high profitability but also expensive.

In this sense, combining these two strategies can provide a competitive advantage, even more so they present a low correlation. As can be seen in table 15, the correlation between value and quality is only 0,10. This article considered world data from 1975 until 2018.

In order to mitigate the risk, which is becoming more important than increasing return, an optimal strategy is create multi-factor portfolio. In the next section, it will be provided a comparison between the two stand-alone portfolios to assess whether there is room for this strategy.

TABLE 16

This table is from an article by MSCI, 'How can factors be combined', done in 2018 by Padmakar Kulkarni, Abhishek Gupta, Stuart Dool. Correlations calculated used 40 years of data and are robust

Exhibit 3: Active Return Correlations for MSCI Factor Indexes since 1975[3]

	Size	Yield	Momentum	Quality	Value	Low Volatility
Size	1.00					
Yield	0.26	1.00				
Momentum	-0.11	-0.03	1.00			
Quality	-0.19	0.40	0.22	1.00		
Value	0.60	0.48	-0.06	0.10	1.00	
Low Volatility	0.12	0.44	0.11	0.19	-0.03	1.00

Correlations of active returns relative to MSCI World, monthly data, 30-Nov-1975 to 28-Feb-2018

11.1.9 Value vs Quality

In order to highlight how the size of the quality factor performs compared to the value factor alone, an analysis of the EW-Long Only portfolio was proposed using the MSCI Europe Value Index and the Stoxx EU 600 as benchmarks. From this analysis, it is, therefore, possible to state that the value factors are drastically outperformed both by equally weighted and cap-weighted portfolio.

The value-index records an average annual return of -0.8%, well below the 7.6% of the P-EW and the 8,7% recorded by the cap weighted portfolio. Furthermore, it is the portfolio that reacts worst to moments of crisis, recording a maximum drawdown of 94%, against 48% of the CW-Long Only portfolio. This is since this value index generates a very high level of risk, with the highest standard deviation, over 20% in annual terms, and therefore the worst Sharpe ratio among the two portfolios (-0.04 vs 0.63 and 0.66 respectively).

It can therefore be confirmed that, in terms of risk and return, the implementation of the quality factor, as a multifactor portfolio, which also includes some value indicators, increases and improves performance compared to the value factor alone.

TABLE 17

	CW - Long Only	EW - Long Only	MSCI EU Value Index
Average Annual Return	8,7%	**7,6%**	**-0,8%**
Standard Deviation	13,2%	**12,1%**	**21,4%**
Sharpe Ratio	0,66	0,63	-0,04
Max DD	-48,2%	**-60,6%**	**-94,0%**
Correlation	11%	9%	

11.2 Long-Short Portfolio

In this section, I implement a market neutral strategy, a long-short strategy, by going long those companies with the highest score and going short those companies with the lowest score. Major hedge funds use this market-neutral to deliver excess returns with lower risk by hedging long bets, considering a bull market and a price increase, with an equal number of short bets.

The following portfolio is created by going long the top 10%, high-quality stocks, and by going short the worst 10%, low-quality stocks. Then, the performance is decomposed in the long side and the short side.

The performance is benchmarked against three indices, two of which are already used previously, Stoxx EU 600 and MSCI Europe Index, and one is Eureka Long-Short Europe Index, which is formed by Eureka Hedge Fund. The latter is the result of a market-neutral strategy, and it seems to be suitable to compare the performance. I could not find data for a long-short quality index which would be the most suitable.

The data for the Eureka Hedge Long-Short Equity index was downloaded using Eikon API but I could not find the daily time series and had to work on monthly prices. From there I calculated the monthly returns for the index as well as for the other portfolios. Standard deviations have been calculated from monthly data and then annualized.

The analysis is carried out following the same procedure as in the previous section for the Long-Only portfolio. As can be seen in Chart 2, It is showed the relationship of the five portfolios to each other. It is showed the cumulative performance from 2000 to 2021 of the long-short style portfolios against the three benchmarks considered. For simplicity, the calculation of the return is exempted by taxes and turnover costs.

The cumulative return (showed in the bottom line of Table 18) is 131,16% for P-EW and 154,17% for the P-CW. The two portfolios outperformed against the benchmark, the Eureka Long-Short index with a cumulative performance of 125,01%. On the other side, P-EW and P-CW

outperformed MSCI Europe and Stoxx Europe 600 by more than 100% in terms of cumulative performance.

An interesting feature is that, during the Dotcom bubble, the long-short portfolio reacts well because of the market-neutral strategy, as opposed to long only, see the previous section or the other two indices. Until 2003, the portfolios outperformed the benchmark with a strong positive performance and then start to decline.

The financial crisis 2007-2008 is a crucial point because P-EW and P-CW reacted positively to the crisis compared to the benchmark. The Eureka growth appears to grow more stable and constant than the quality portfolios, although it is not an exponential growth.

The highest average annual return is the P-CW with 7,52% for, followed by P-EW with 6,39% and Eureka Long-Short Index with 6,12%

The standard deviation is lower for P-EW than the benchmarks with 10,13%, resulting in higher result in risk-adjusted return term. Conversely P-CW has a higher standard deviation than Eurekahedge long short (14,18% instead of 11,19%)

The best Sharpe ratio is 0,63 of the Equally weighted portfolios and the second is the Eureka Index with 0,55, followed by the Cap-Weighted with 0,53. The simplest weighting scheme improved on risk-adjusted returns, given the low volatility, as opposed to the Long-Only specification.

The percentage of months in which the return was positive is high for the Eureka Index with 82% of months with positive returns, while P-EW and P-CW are on average 52% of positive months.

The maximum DrawDown in the long-short is halved compared to the long only, giving greater robustness, with a 30% for P-EW and 46% for P-CW. Otherwise, the maximum Drawdown for Eureka Index is 48%.

The return adjusted by the maximum DrawDown is 21,20% for the P-EW, the highest among the portfolios, followed by Eureka Index with 12,62%% and P-CW with 16,18%.

To conclude, it is not possible to affirm that one of the portfolios performs better than others, but it should be decomposed singularly in order to make a deeper analysis, and, eventually, to choose the best according to the risk profile assumed by an individual.

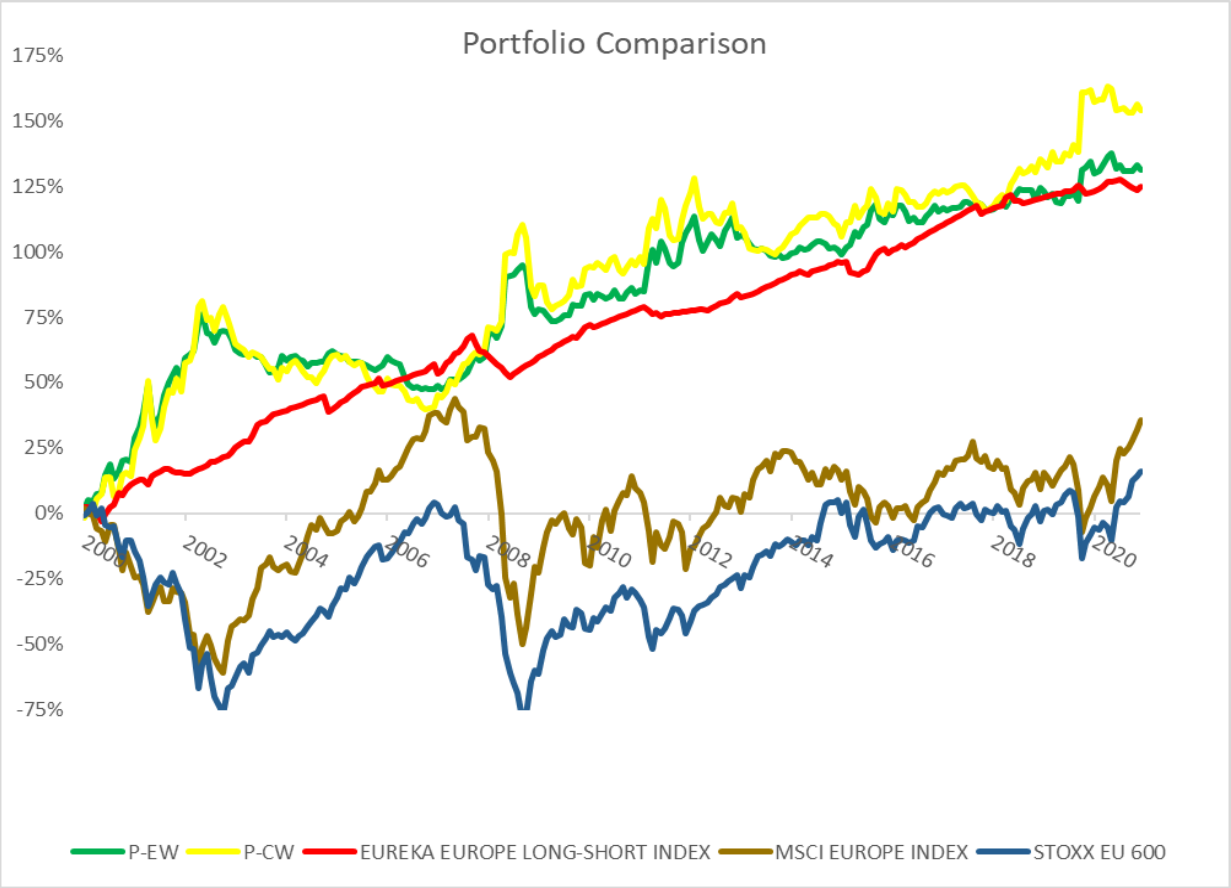
Moreover, as the previous section, the portfolios perform similar to the low-volatility factor, since both portfolios perform better during drawdowns and instead during market recovery underperform against other factors-based portfolio, such as size, momentum and Value. This characteristic will be treated in a separate section later.

TABLE 18

In this table are presented the results of 5 different portfolios. The analysis covers from June 2000 to June 2021. The average excess return is calculated by averaging the years considered, once all the annual returns have been aggregated minus the risk-free rate. The standard deviation is annualized multiplying by the monthly standard deviation with the square root of 12. The Sharpe ratio is the ratio between average annual excess return and the standard deviation. The positive months are calculated with SUMIF excel function. The formula for the maximum drawdown (Max DD) is: $D(T) = max\{0, max\, X(t) - X(T)\}$ $where\, t \in (0,t)$. The Calmar ratio is the ratio between average excess return and the absolute value of the maximum drawdown. The cumulative return is calculated as the sum of monthly portfolio returns from the first period of time up to the last given month .These indicators are explained in the previous section.

	P-EW	P-CW	STOXX 600	MSCI EUROPE INDEX	EUREKA L-S EUROPE
Average Annual Return	6,39%	7,52%	0,82%	1,74%	6,12%
Standard Deviation	10,13%	14,18%	19,56%	22,52%	11,19%
Sharpe Ratio	0,63	0,53	0,04	0,08	0,55
Positive Days	51,74%	51,52%	52,23%	52,50%	-
Positive Months	53,75%	52,96%	56,13%	54,15%	82,54%
Max DD	30,12%	46,46%	93,97%	103,48%	48,44%
Calmar Ratio	21,20%	16,18%	0,87%	1,68%	12,62%
Cumulative Return	131,16%	154,17%	16,12%	35,69%	125,01%

GRAPH 2



11.2.1 Compound return

To consider the compounding effect over time, I present below the time series of the compounded return. As opposed to the average annual return, the compounded one is a more accurate measure of performance because investors, with only average return, can over or underestimate growth or decline in return. Compound returns take volatility into account in the calculation.

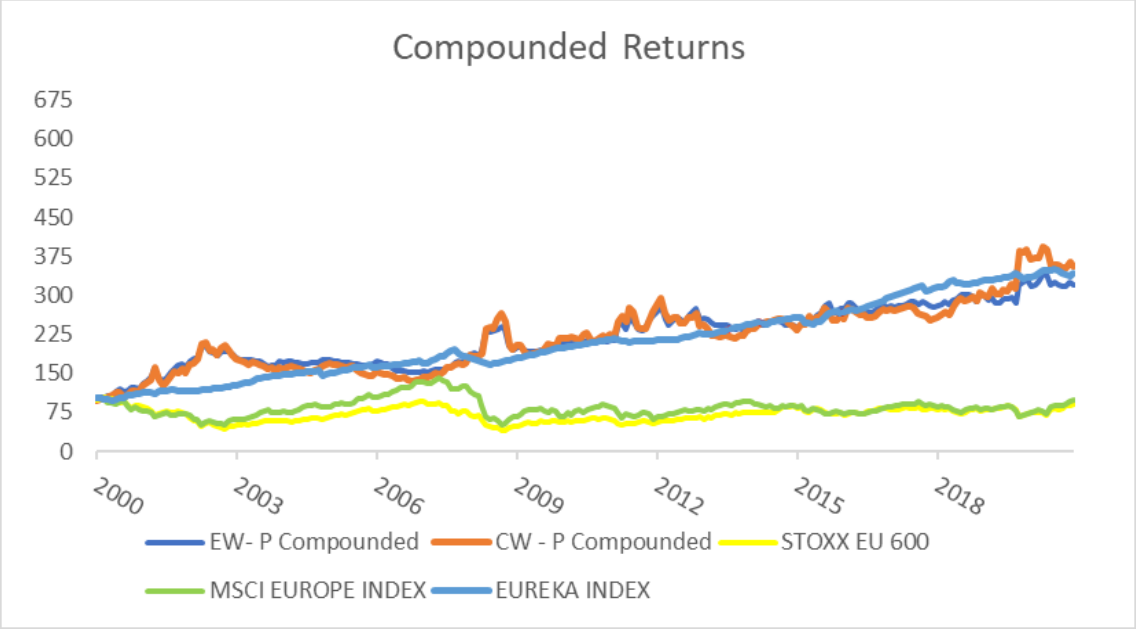
If you had invested $100 in the Quality sort portfolios P-EW in June 2000 would have been worth in June 2021 320$ and seems to be interesting but not as good as the P-CW with a 360$.

Only the P-CW portfolio outperformed against the equity index. If you had invested $100 in the Eureka Europe Equity index in June 2000 would have been worth in June 2021 341$.

The MSCI Europe index and the Stoxx EU 600 underperformed against other portfolios with a worth of 90$ and 98$, respectively, at the end of the period.

The best portfolio in the time series of compound returns is the P-CW followed by the Eureka Long-Short Europe Index. The average annual compound return is 12% for the P-CW, which is surprisingly good compared to other portfolios in Europe.

GRAPH 3



11.2.2 Equal-Weighted Long-Short Portfolio

11.2.2.1 Performance, year-by-year

Table 19 shows the performance of each portfolio decomposed into total, long and short. It is also divided by each year as in the previous paragraph. The analysis focuses on returns and volatility to get a broader view and the source of the performance.

During the Dot-Com Bubble, the long-short performed well thanks to the extraordinary performance of the short side, which offset the negative performance of the long-only. The characteristic of the long-short is that it is market neutral and provides protection against crises as deep as the one in 2001.

The years between 2001 and the subprime mortgage financial crisis performance is far below expectations, driven mainly by a significant outperformance of the short side, but with below-average volatility. In 2007 the volatility reaches 4,28%, the lowest except for the first six months of 2021.

During the financial crisis of 2008, the performance was remarkable, with a peak of 39%, thanks again to the short side, which in this case reached an incredible -75%. In this period in which the market volatility was so high, the portfolio long-short reacted above the expectations giving more stability and the volatility was around 20%.

On the other side, in the following year in the rebound period the portfolio performed negatively with a -15,79%, driven by the -50% of the short side which offset the +30% of the long-only.

In the following years the return is positive but not high, maintaining a high Sharpe ratio thanks to very low volatility. The main problem is given by the short side because the long-only performed quite well from 2011 to 2021, with an average annual return of 11%.

The decomposition highlights the sources of the problem of the long-short specification as well as the source of income. The market-neutral strategy is less volatile but loses something in returns compared to the long only.

TABLE 19

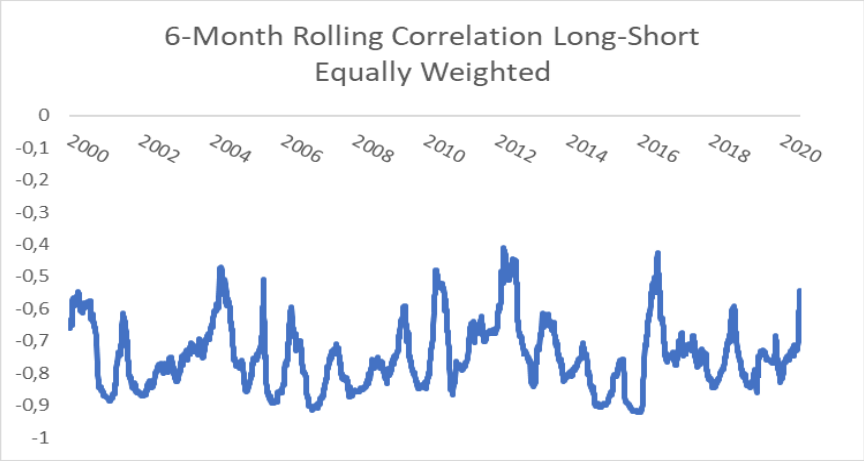
Total Portfolio is the difference between long and short portfolio. The short side is shown with a minus sign. In green the value is positive while in red is negative.

Year	Total Portfolio		Long-Only Equally Weighted		Short Portfolio	
	Annual return	Annual volatility	Annual return	Annual volatility	Annual return	Annual volatility
2000	18,54%	8,18%	2,26%	9,91%	16,28%	15,40%
2001	19,31%	22,16%	-8,25%	21,66%	27,56%	41,20%
2002	30,38%	16,75%	-25,39%	25,15%	55,77%	34,46%
2003	-8,66%	7,38%	21,11%	16,41%	-29,78%	18,32%
2004	-2,13%	7,70%	9,76%	7,69%	-11,89%	13,83%
2005	-0,15%	4,44%	21,45%	9,85%	-21,59%	12,09%
2006	-9,22%	6,87%	18,81%	9,82%	-28,03%	13,39%
2007	4,28%	4,28%	3,51%	12,62%	0,77%	12,99%
2008	39,02%	19,75%	-35,79%	25,16%	74,81%	42,39%
2009	-15,79%	15,16%	34,96%	17,98%	-50,74%	31,24%
2010	9,45%	6,61%	15,60%	15,56%	-6,15%	20,15%
2011	16,38%	17,14%	-13,92%	18,26%	30,29%	34,22%
2012	3,18%	16,69%	20,32%	11,80%	-17,14%	26,37%
2013	-4,14%	11,61%	18,08%	13,82%	-22,23%	19,03%
2014	3,54%	4,29%	7,79%	10,26%	-4,25%	10,40%
2015	6,51%	7,80%	7,42%	12,69%	-0,91%	16,50%
2016	0,63%	11,09%	10,30%	8,12%	-9,67%	16,33%
2017	7,72%	4,69%	14,89%	6,26%	-7,17%	6,44%
2018	5,31%	6,31%	-13,14%	13,18%	18,45%	17,48%
2019	-2,99%	8,17%	21,85%	11,17%	-24,84%	16,47%
2020	11,76%	15,50%	9,90%	32,65%	1,86%	44,52%
2021	-2,41%	3,70%	13,68%	5,98%	-16,09%	6,45%

11.2.2.2 Rolling Correlation Long-Short Equally Weighted

The following Table 20 is the 6-Month rolling correlation between the long-only portfolio and the short portfolio. As can be seen, the correlation is highly negative, and it helps for diversification purpose, reducing the portfolio volatility.

TABLE 20



11.2.3 Cap-Weighted Long-Short Portfolio

11.2.3.1 Performance, year-by-year

Similarly, in table 21 the returns are analysed separately for long and short sides and then for each year as done in the previous paragraph. The long-short portfolio's performance is decomposed to see any improvements on risk-adjusted returns and portfolio volatility.

As in the previous paragraph, the Dot Com bubble thanks to the short side allows to compensate the losses of the long side, reducing the standard deviation from 2000 to 2002 and the average return is 25%. Considering the time of crisis, the result appears satisfactory with an average volatility of 20%.

During the financial crisis, the splendid performance of the short side once again enables positive returns to be recorded on the long-short with a 42,22% and a volatility of 26,04%.

The rebound period is poor for the returns, as seen before, and cancels out the good performance of the long only because of the short side with a -50,74%.

The following two years the performance is quite well, mainly driven by the long-only with a +17,20% and a +18,32%.

From 2012 until 2021, the short side does not help in improving returns but helps in reducing volatility and, overall, in improving the Sharpe ratio. The average annual return is 7,72% and the volatility is 11%. The Sharpe ratio is 0,70, resulting in higher risk adjusted return.

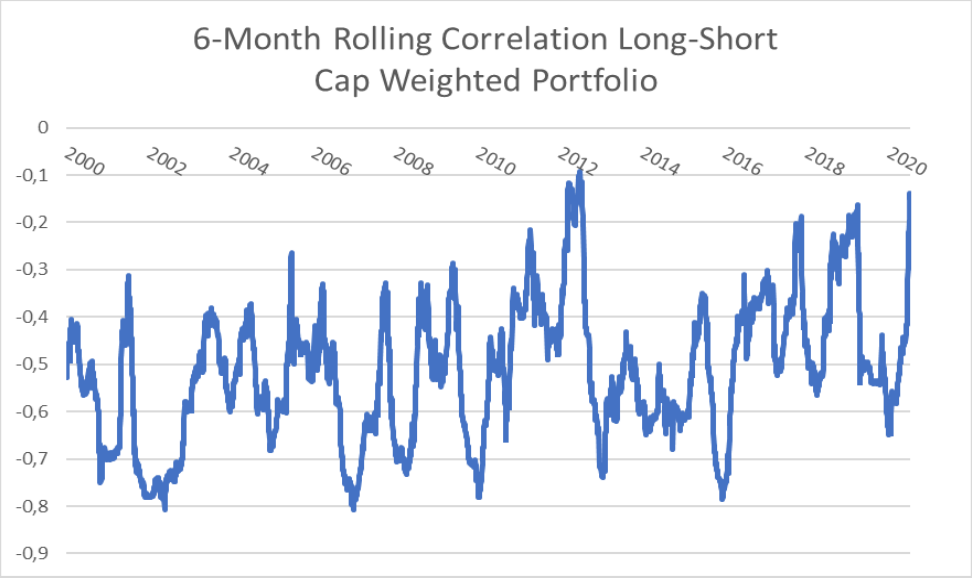
TABLE 21

ANNUAL PERFORMANCE (%)						
Year	Total Portfolio		Long Portfolio		Short Portfolio	
	Annual return	Annual volatility	Annual return	Annual volatility	Annual return	Annual volatility
2000	13,58%	8,36%	-2,71%	9,27%	16,28%	15,40%
2001	18,77%	29,85%	-8,79%	15,72%	27,56%	41,20%
2002	42,35%	22,67%	-13,42%	21,82%	55,77%	34,46%
2003	-14,85%	11,88%	14,92%	15,97%	-29,78%	18,32%
2004	-7,89%	8,54%	4,00%	8,86%	-11,89%	13,83%
2005	5,64%	6,96%	27,23%	11,98%	-21,59%	12,09%
2006	-14,78%	8,58%	13,25%	11,36%	-28,03%	13,39%
2007	14,14%	8,84%	13,37%	10,15%	0,77%	12,99%
2008	42,22%	26,04%	-32,59%	21,62%	74,81%	42,39%
2009	-18,22%	23,31%	32,53%	10,94%	-50,74%	31,24%
2010	17,20%	9,79%	23,36%	12,66%	-6,15%	20,15%
2011	18,32%	20,24%	-11,97%	16,75%	30,29%	34,22%
2012	-5,46%	20,67%	11,68%	10,02%	-17,14%	26,37%
2013	-10,29%	13,15%	11,93%	13,43%	-22,23%	19,03%
2014	12,46%	4,26%	16,71%	8,45%	4,25%	10,40%
2015	4,25%	11,90%	5,16%	14,15%	0,91%	16,50%
2016	-0,10%	14,58%	9,57%	10,26%	-9,67%	16,33%
2017	6,77%	4,19%	13,94%	7,05%	-7,17%	6,44%
2018	7,63%	9,78%	-10,82%	12,19%	18,45%	17,48%
2019	4,93%	10,56%	29,78%	7,86%	-24,84%	16,47%
2020	17,96%	26,48%	16,10%	21,60%	1,86%	44,52%
2021	-0,98%	4,38%	15,11%	7,57%	-16,09%	6,45%

11.2.3.2 Rolling Correlation Long-Short Cap Weighted

The following Table 22 is the 6-Month rolling correlation between the long-only portfolio and the short portfolio. As shown, in the cap weighted scheme, the correlation is less significant than the equally weighted but there is still room for diversification with a peak of -0,8.

TABLE 22



11.2.4 Fama French Factor Loading

11.2.4.1 Cap Weighted Long-Short Portfolio

In this section, as shown in Table 23, I ran this regression for the excess return of the Cap-Weighted long-short portfolio. The data are downloaded from Kenneth R. French website for the European 5-factor monthly returns. Therefore, I pooled the monthly data and calculated the excess returns by subtracting back the risk-free rate (from Kenneth R. French website).

I first ran a regression on the market risk premium. The beta is - 0,51, less than 0, statistically significant at 5% level, meaning that the portfolio moves in the opposite direction from the stock market. The portfolio acts as a hedge against severe market downturns. Additionally, the Jensen's Alpha is 9% per annum, meaning the portfolio is not fully explained by only market risk premium. Next, I ran multiple regressions in order to control for the standard factors, such as size, value, profitability and investments.

The size factor is statistically significant and highly negative –0,51, meaning that the portfolio is exposed to companies with high market capitalization, which is one of the characteristics of the Quality Factor.

The value factor is significant at 5% level. It has a negative value that ranges from -0,30 to -0,43, except for -0,08 in the 4th regression, which reflects the inclination to buy expensive companies and sell cheap companies as the quality factor in literature.

Moreover, the portfolio has a statistically significant loading on RMW, the profitability factor with 0,8 and a t-statistics of 4,91. The Cap Weighted portfolio tends to buy companies with higher profitability than those with lower profitability. The portfolio shows the positive loading on CMA, the investment factor, reflecting the tendency to buy companies with low level of investments and sell companies with high level of investments.

The alphas are annualized and are monotonically decreasing. As it can be seen, these five factors don't explain so much of the alpha shown in Table 23. The alpha is 9,03% for the first regression and 6% for the last regression. The Jensen's Alpha doesn't become insignificant when controlling for the quality factors, the profitability and investment factor, meaning that the source of alpha generation needs to be sought in other factors or the portfolio is a factor itself.

Further on it, I will show the possible explanations of this alpha generated by the long-short portfolio.

TABLE 23

Cap Weighted Portfolio, 6/2000-5/2021 (t-statistic in parentheses)						
Alpha*	**9,03**	**10,38**	**11,32**	**6,93**	**6,00**	
	(3,12)	(3,71)	(4,12)	(2,51)	(2,22)	
Mkt-RF	**-0,51**	**-0,52**	**-0,48**	**-0,41**	**-0,30**	
	(11,44)	(11,96)	(10,81)	(9,15)	(6,13)	
SMB		**-0,54**	**-0,55**	**-0,54**	**-0,46**	
		(4,62)	(4,84)	(4,98)	(4,27)	
HML			**-0,30**	-0,08	**-0,43**	
			(3,44)	(0,84)	(-3,48)	
RMW				**0,80**	**0,74**	
				(4,91)	(4,68)	
CMA					**0,73**	
					(4,17)	
R Square	0,60	0,63	0,65	0,69	0,71	
Obs.	252	252	252	252	252	
*Alphas are annualized. Boldface indicates statistical significance at the 5% level						

In the following table 24, in order to be more consistent and robust in the analysis, I used the excess returns to run the regression controlling for the 5 already known factors. The R squared is only 0,31 with 5288 observations, which are the calendar days from June 2000 to April 2021. The data are retrieved from Kenneth R. French website.

The annualized alpha is positive with 4,89% on annual basis and statistically significant. The generated alpha is still positive and consistent when you control for the standard factors.

The market beta is negative but weaker in magnitude than the beta calculated in the previous section (-0,01 instead of -0,51). The portfolio seems to have the same characteristic to act as hedge against market downturns but with less powerful.

The size factor (SMB) is negative (-0,14) and statistically significant at 5%. The portfolio still has this tendency to buy companies with high market capitalization and sell companies with low market capitalization.

The value factor (HML) is not only low but also statistically insignificant with a t-stat of 0,22. The non-exposure to the value factor could enable to gain extra return when you will increase the exposure to it, adding some value indicators such as Price-to-Earnings or Dividend Yield.

The profitability factor (RMW) is in line with the previous regression analysis. It is positive with a coefficient of 0,26 and statistically significant with a low p-value. This evidence the tendency of the portfolio to buy companies with high profitability and sell companies with low profitability.

The investment factor (CMA) is positive (0,19) and statistically significant at 5% level. This means that in the portfolio are included conservative firms more than aggressive ones.

The conclusion is that with both daily and monthly returns the exposure to factors is robust and consistent as they change. The alpha becomes lower considering excess daily returns with almost 5% less than excess monthly returns.

TABLE 24

SUMMARY OUTPUT	
Regression Statistics	
R Square	0,31
Adjusted R Square	0,30
Standard Error	2,35
Observations	5288

Factors	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Alpha *	**4,89**	2,11	2,32	0,01
Mkt-RF	-0,01	0,01	-0,94	0,35
SMB	**-0,14**	0,03	-5,24	0,00
HML	-0,01	0,03	-0,22	0,82
RMW	**0,26**	0,05	5,88	0,00
CMA	**0,19**	0,04	4,55	0,00

* Alpha is annualized

11.2.4.2 Equally Weighted Long-Short Portfolio

In the following Table 25, it is shown the exposures to the standard factors for the equally weighted portfolio, as done previously. The first conclusion is that the results are robust but less amplified in magnitude compared to the Cap-Weighted portfolio. The data were previously downloaded from the Kenneth website. R. French.

As shown in Table 25, I ran multiple regression sequentially from the first to the fifth of the excess return, $R_t - R_t^f$, of the equally weighted long-short portfolio on the different factors.

The first regression is the CAPM one with only the market factor as independent variable. The beta, associated with this factor, is higher than the cap-weighted (-0,35 instead of -0,51), reflecting the tendency of the portfolio to act as hedge against market turbulence. The annualized Jensen's alpha is 6,94%, statistically significant at 5% level.

After controlling for the size factor (SMB), the market beta remains constant while the alpha is even higher. The SMB coefficient is -0,30, with a t-statistics of 3,31, meaning that the portfolio is exposed to companies with high market capitalization and tends to sell companies with small market capitalization. This evidence the characteristics of the quality factor, as shown before, to buy bigger companies than smaller, which are riskier and less safe.

The portfolio is also negatively exposed to the value factor (-0,18 and a t-stat of 2,61), reflecting the inclination to buy expensive and sell cheap companies. The alpha is higher 8,26% on annual basis.

When I control for the profitability factor, the alpha is almost halved meaning that RMW factor explains part of the performance and therefore the alpha is smaller. The RMW is 0,63 and a t-statistics of 4,83. As a result the portfolio tends to buy profitable companies and sell unprofitable one.

The investment factor is positive (0,61) and statistically significant at 5% level, showing that it prefers to invest in safer stock with low level of investment.

In conclusion, the results are robust with the definition of quality factor made by the literature and in line with the results shown in the previous section.

TABLE 25

Equally Weighted Portfolio, 6/2000-5/2021 (t-statistic in parentheses)						
Alpha*	**6,94**	**7,70**	**8,26**	**4,83**	4,04	
	(3,12)	(3,51)	(3,79)	(2,19)	(1,89)	
Mkt-RF	**-0,35**	**-0,35**	**-0,33**	**-0,27**	**-0,19**	
	(10,17)	(10,31)	(9,40)	(7,75)	(4,77)	
SMB		**-0,30**	**-0,31**	**-0,30**	**-0,23**	
		(3,31)	(3,44)	(3,51)	(2,75)	
HML			**-0,18**	-0,01	**-0,31**	
			(2,61)	(0,11)	(3,10)	
RMW				**0,63**	**0,58**	
				(4,83)	(4,60)	
CMA					**0,61**	
					(4,47)	
R Square	0,55	0,57	0,59	0,63	0,67	
Obs.	252	252	252	252	252	
*Alphas are annualized. Boldface indicates statistical significance at the 5% leve						

Table 26 presents the regression of equally weighted portfolio's daily returns on kenneth french returns. The data are retrieved from Kenneth R. French website and are 5 different portfolios' returns. The R squared is 0,28 and the observations are 5288, as the calendar days.

The market Beta is small and negative, but it is statistically insignificant at 5% level. The regression analysis fails to establish a significant relation between the market and the portfolio.

The size factor (SMB) is negative, as shown previously, with a coefficient of -0,085, showing the tendency to buy larger companies than smaller.

The value factor is still negative but not statistically significant with a t-statistics of 1,339 and a coefficient of -0,03.

The profitability factor is 0,130, positive and statistically significant. The significant loading shows the inclination to buy companies with high profitability and sell companies with low profitability.

The investment factor is 0,155, it is still positive and robust with the previous regression analysis.

The Jensen's Alpha is lower than the last regression, but it is still positive with an almost 3% per annum and a t-statistics of 2,571

TABLE 26

SUMMARY OUTPUT	
Regression Statistics	
R Square	0,28
Adjusted R Square	0,27
Standard Error	2,21
Observations	5288

Factors	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Alpha *	**2,978**	1,159	2,571	0,000
Mkt-RF	-0,016	0,010	-1,596	0,110
SMB	**-0,085**	0,019	-4,499	0,000
HML	-0,030	0,023	-1,339	0,180
RMW	**0,130**	0,032	4,021	0,000
CMA	**0,155**	0,030	5,137	0,000

* Alpha is annualized

11.2.5 Tracking Error

In this strategy, the tracking error is lower than the long only strategy, meaning that the portfolio is following its benchmark closer than the long-only. In this case, the benchmark is the Eurekahedge long-short Europe equities because, in order to benchmark a long-short strategy you should use the same market neutral strategy.

The annualized TE is 18,8% for the Cap-Weighted portfolio, while only 14,8% for the Equally weighted portfolio.

EUREKA HEDGE FUND	**TE (monthly)**	**TE At VaR***	**TE (annualized)**
Cap-Weighted	5,42%	8,9%	18,8%
Equally-Weighted	4,26%	7,0%	14,8%

*TE at Value at Risk is the extreme expected Te at 95th percentile

11.3 Quality and Stock Return

In this section, it is carried out the univariate portfolio analysis sorting by quality factor. The quality factor is built using the same criteria as the portfolios, illustrated above.
The variables are:

- Gross Profit-to-Total Assets
- ROA
- Operating Cash Flow-to-Debt
- Debt-to-Equity
- YoY Earnings Variability

Table 27 shows the results of two different analyses using two different weighting schemes: value-weighted and equally weighted.

There is the linear relationship between quality factor and future stock returns. As can be seen in Table 27, the relationship is statistically significant and positive. Panel A shows an average Cap weighted return of 5,97% per year, with a T-statistics of 5,44, meaning that is statistically significant at 99% level. In Panel B, the average excess return is 5,05% per year (t-statistics of 6,41), statistically significant at 99% level. The returns are increasing monotonically from low-Quality portfolio to high-Quality portfolio, except for the second portfolio (80^{th} percentile).

TABLE 27 **Univariate Portfolio Analysis**

This table presents the results of univariate portfolio analysis of the relation between Quality and future stock returns. Yearly portfolios are constructed by sorting all stocks in Stoxx EU 600 sample into portfolios using Quality decile breakpoints calculated using all stocks in the sample. **Panel A** shows the average value-weighted one-year-ahead excess returns for each of the 7 decile portfolios as well as for the long-short zero-cost portfolio that is long the top decile portfolio and short the bottom decile portfolio. T-statistics are calculated, testing the null hypothesis that the average portfolio excess return is equal to zero. **Panel B** presents the results for equally weighted portfolios. The analysis is carried out using the same breakpoints and the same decile as of cap- weighted. The numbers are in percentage.

Panel A: Value Weighted Portfolio Returns sorting by Quality

	Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average		1,39	2,15	3,88	4,03	4,61	7,36	5,97
T-Stat		1,92	1,84	2,68	3,06	2,80	4,47	5,44

Panel B: Equally Weighted Portfolio Returns sorting by Quality

	Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average		3,37	5,88	6,38	6,44	7,66	8,42	5,05
T-Stat		2,29	3,99	4,42	5,41	5,75	6,29	6,41

12. CONCLUSION

This chapter discusses the empirical results of the previous findings. Additionally, discussions around the possible limitations to the study are made. Eventually, potential explanations are discussed.

12.1 Results

The results are discussed in this section. The thesis uses the Sharpe Ratio as the main indicator for risk-adjusted performance. All the quality portfolios have positive Sharpe Ratio and greater than benchmark portfolios. The best performing portfolio is the Long-Only Cap Weighted with a Sharpe Ratio of 0,66, followed by the Long-Only Equally Weighted with 0,63. Using a market neutral strategy, the Sharpe Ratio are lower but still greater than the benchmark 0,627 (Equally Weighted Long-Short and 0,53 (Cap Weighted Long short).

This thesis uses Fama-French five factor model as the main asset pricing model. All the strategies produce significant and positive Alphas. Additionally, a robustness check is made, using monthly and daily data. The results are robust and consistent, producing both significant Alphas. Moreover, the significant loadings are mainly on profitability and investment factor, meaning that the portfolios tend to buy profitable and conservative firms and to sell short unprofitable and aggressive firms.

12.2 Limitations to the study

The main issue is the database used in this thesis. The dataset was retrieved from Eikon Refinitiv, using Eikon Data API. Some companies were excluded as the companies did not have historical prices available and others were dropped out as they had no financial variable data. The sample was the Stoxx Europe 600, a stock index composed by the 600 largest companies in the European market. Therefore, one additional limitation is the dataset composed by only 600 companies, of which a range of 10%-15% were excluded each year, due to lack of data. Moreover, the transactions cost were not included in the model for simplicity as it's a more theoretical study aimed at discovering a new factor.

Another potential issue is the period. To have reliable results, the time period should be extended to 40 years, even if from 2000 until 2021 it's still a fair time interval.

Lastly, the benchmark used in the Long-Short strategy is the Eurekahedge Long Short Europe index fund. It is not a proper benchmark for two main reasons: only monthly data are available and is not a Quality index.

12.3 Concluding remarks

This research thesis is aimed at discovering a new factor to generate positive alpha in the long-short strategy. As far as the author of this thesis was aware, no previous studies regarding the test of a new factor through quantitative analysis in the European market had been conducted. The anomaly generated by quality portfolios can be explained from two different points of view: the risk-based view and the behavioural view. The former is in line with the efficient market hypothesis and states that the abnormal excess returns, generated by the long-short strategy, is the compensation for risk, which is to say that investing in quality firms is riskier. The latter states that investors are not rational and undervalue the high-quality firms. This view contradicts efficient market hypothesis.

Capital Fund Management and CFM-Imperial Institute of Quantitative Finance[27] found that is hard to account for this anomaly using a risk premium argument, which are characterized by a negative

[27] Jean-Philippe Bouchaud , Stefano Ciliberti , Augustin Landier , Guillaume Simon, and David Thesmar, "The Excess Returns of Quality Stocks: A Behavioral Anomaly", 2016.

skewness and a propensity to crash, while returns of quality strategies have all positive skewness. By contrast there is evidence that investors don't pay attention to firm-level profitability such as cash flow to assets. This behavioural bias could be because analysts are too focused on other indicators such as EPS, Book-to-Market, Momentum and volatility. Additionally, people and investors form biased beliefs and tend to overestimate the quality of the private information, while don't consider properly public information. Because of this biased behaviour, stock prices might take time to adjust reflecting the true value of the companies. Eventually, investors systematically underestimate future earnings growth and returns of high-quality firms, compared to low quality.

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SUMMARY

This is a research thesis aimed at investigating market anomalies. The idea is to investigate market anomalies, implement an investment strategy, using a programming language through a quantitative analysis and back test the strategy over the last 20 years in the European stock market. There is an extensive literature with examples of how to earn excess return and exploit anomalies in the market, but it is only in the recent period such an interest in the factor investing. Factor investing is a strategy that chooses firms based on characteristics that are associated with subsequent abnormal returns. The recent development is because this investment methodology is based on simple and economically sensible criteria. In the future it will be increasingly applied and evolve with the use of Big Data. In addition, factor investing has taken off to contain the high costs of active portfolio managers while maintaining management techniques used by them but at lower costs. It is a kind of mix between passive and active management, where passive management is a style management based on mutual or exchange traded fund (ETF). According to the Efficient Market Hypothesis (EMH), a market is efficient because all market prices reflect all available information. This theory has received criticism since some anomalies exist and markets are not correctly priced. Anomalies such as small-firm-in January effect, book-to-market and price to earnings are popular findings in the finance literature. In the light of this, I wanted to explore a market anomaly that is present but not fully defined: the quality factor. The results achieved by the various portfolios, that will be examined and analysed in detail, are surprisingly positive. In the Long Only strategy, the results show a clear outperformance compared to the overall market in the European stock market with a Sharpe ratio for Cap-weighted portfolio and equally weighted portfolio respectively of 0,63 and 0,66. In the Long-Short strategy, the portfolios outperformed the benchmark in terms of risk adjusted return (0,63 compared to 0,53). Market capitalization weighted and equally weighted are the main weighting scheme used in this work. Moreover, the Jensen's Alpha generated by the two strategies is positive and high: it reaches 6% in the Long-Short while in the Long Only is 5%.

This thesis aims to investigate whether the quality factor is a real premium factor and whether there is an anomaly in the market. The focus of the analysis will be on the European market since, despite the extensive literature in the US, there is no in-depth study of empirical asset pricing.

Since the factor has multiple shades with different variables to be included within the modelthe purpose of the investigation is to see which ones are the best at explaining future stock returns, i.e the best at predicting the returns.

The analysis is carried out using a common methodology in empirical asset pricing, which is called Univariate Portfolio Analysis. After the proper selection of the variable, the thesis work will be to build a stock portfolio and back test it to see how it performs over time. The aim is to see if it has a positive alpha and if there is an extra return, in relation to different benchmarks.

I will implement the study by analysing the data from Refinitiv Eikon Data Provider and by using Python, as the main programming language, together with Microsoft Excel. Every year, I rank the European companies, from the Stoxx Europe 600, in order of some criteria of profitability, earnings stability and capital structure. The top 10 percent of the companies are selected into the long-only portfolio and the bottom 10 percent are selected in the short portfolio. I also construct a long-short portfolio, a portfolio that is sometimes difficult to implement for retail investors but is extremely important to test the performance of the factor. For this reason, from a client investor's perspective, first I will present the Long-Only strategy, which seems to be simpler to implement in terms of constraints. The Long-Short portfolio is part of a market neutral strategy that aims to seek profit from increasing and decreasing prices, while avoiding any kind of market specific risks.

As Fama and French indicates from their papers, the start date of the holding period is the last trading date of June for each year. The data are available from 1999 until 2021 and the portfolio formation is based on the previous year.

Factor investing has become increasingly popular for over 20 years among both equity and fixed-income investor who have realised that they could have increased the desired exposure, reduce risk, increase return. A factor can be thought of as a characteristic of an aggregate of assets that is important in explaining return and risk. To be better understood, I describe the factor quoting an author[1], through an analogy, "the factors are to assets what nutrients are to foods".The popularity was driven also by successful investors such as Warren Buffett, Seth Klarman and Joel Greenblatt.It is a relatively new concept that is rapidly spreading, and it is based on factors premium, for example value, momentum and volatility in equity market, that have demonstrated

[1] Andrew Ang, 'Asset Management: A systematic approach to factor investing', 2014

to be robust over time and across different markets. There are different types of factors: macroeconomic factors (GDP growth, inflation and volatility), cross sectional factors (Size, Value and Momentum) and Statistical Factors(Derived empirically from the covariance matrix).

The quality factor is one of the strongest and most scalable reported anomalies in capital markets. It refers to the tendency of high-quality stocks with stable earnings and cash flows, sound balance sheet, higher margin to outperform low-quality stocks over long term. Researchers Assness and Frazzini[2] define the quality factor as investing in the stocks of safe, profitable, expanding and well-managed companies or all those "characteristics that make a company valuable". Quality investing starts in 1930s when Benjamin Graham, the father of value investing and the greatest financial consultant in 1900s, divided high quality companies and low-quality stocks and distinguished between cheap and quality stocks. As he has stated on several occasions, Buffett is inspired by Benjamin Graham. His strategy is to buy cheap, safe and high- quality stocks. He is considered the father of what can be called "quality investing at a good price", with this referring to the value dimension. Warren Buffett realized an average annual return of 18,6%, outperforming the stock market's return of 7,5%[3]. One dollar invested in 1976 would have been worth almost 4000$ today. The surprisingly performance should not be confused with lucky but with a targeted stock selection. This can be demonstrated by the alpha that becomes insignificant when you control the exposures for "quality minus junk" and "betting against beta". The results of Warren Buffett appear to be a reward for investing in high-quality companies.

After the Dot-Com Bubble in 2001, quality factor became increasingly popular as investor started to pay more attention to the quality of earnings, sound balance sheet, information transparency, good management team etc... This is the reason why a well-managed quality strategy provides great protection from the risk faced by value investors. Sometimes, companies are cheap for a specific reason and the Dot-Com Bubble highlighted this negative side.

In academia, Eugene Fama and Kenneth French introduced the quality premium with the operating profitability factor, calculated as revenues minus cost of goods sold divided by the book value of equity. The top quintile significantly outperformed other quintiles by 5,5% from 1990 to 2019.

[2] Clifford S. Asness, Andrea Frazzini, and Lasse H. Pedersen: 'Quality Minus Junk', 2013

[3] Andrea Frazzini, David Kabiller, CFA, and Lasse Heje Pedersen, 'Buffet's Alpha', 2018

The quality factor is usually identified as an autonomous source of return, that also aid to diversify the portfolio due to the low correlation with other factors, value and momentum. However, according to Hsu, Kalesnik, and Kose (HKK)[4] the quality factor lacks definitions, compared to well-known and accepted value, size, and momentum factors. Their study in the literature was able to show that variables, such as profitability, investment (i.e. asset growth), accounting quality, and payout/dilution, are strongly correlated with future returns. Regarding capital structure, the empirical results are doubtful, but a deeper look may reveal that these are also related to the low-beta anomaly. Moreover, earnings stability is also considered a factor and low beta. Finally, HKK found that the most correct quality definition is a combination of the profitability and investment signals.

This analysis is focused on 600 companies in the Stoxx Europe 600, an index composed by large, mid and small capitalization companies among 17 European countries, which covers 90% of the overall capitalization in the European market. This reflects the choice to analyse the quality factor in European market, as most of the researchers has been focused on American market. It was introduced in 1998, so the analysis starts with 1999 in order to have more screened data and due to the unavailability of the data. A long history is the prerequisite to demonstrate an alpha or the existence of a factor premium.

In order to be consistent with empirical asset pricing, I made a series of hypothesis and test to identify a list of potential factors to elaborate a ranking based on the quality factor. I've taken into consideration 5 fundamental indicators to build this quality indicator. The macro-categories are profitability, earnings quality, capital structure and accounting quality.

[4] Jason Hsu, Vitali Kalesnik , and Engin Kose, 'What is quality?', 2019

The indicators are presented in Figure 1 and are Gross Profitability-to-Assets, ROA (Profitability factor), YoY Earnings Variability (Earnings Stability), and Debt-to-Equity, Operating Cash Flow-to-debt (Capital Structure).

Then I build a multi-factor portfolio through a simple methodology. It is performed using this approach:

1. I calculate the sector median for each variable.
2. I compare each company with the sector median of its interest.
3. I assign a different score based on the threshold it reaches.
4. I elaborate a final ranking consisting of the best 10% and the worst 10%.

1. SCORING SYSTEM

The scoring system is as follows (see Figure 1): for each of the 5 variables from 3 different macro-categories, I assign a score of 1 if it is excess by at least 50% the industry median, a score of 0.5 if it is above 20% and below 50% from the industry median. Then I assign a negative of -1 if it is 50% lower than the industry median and only -0.5 if it is lower than 20% from it.All of the variables are assigned with equal weights, 20% per each variable, for the construction of the combined rank.For Debt-to-Equity and the standard deviation Year over Year Earnings, the logic used is the inverse, giving a negative score to the one that is higher than the peers and a positive score to the other that is lower than the peers. Thus, I have defined quality as a combination of signals from different categories.

Figure 1

Reference Variables and Rules - Score Point Grading System	**WEIGHTS: ---------->**	
Profitability	Rules	Scorepoint
Gross Profit-to-Total Assets	Higher than 50% from peers	1
Return on Assets	Higher than 20% from peers	0,5
Capital Structure	Lower than 20% from peers	-0,5
Operating Cash Flow-to-Debt	Lower than 50% from peers	-1
Debt-toEquity		
Earnings Stability		
YoY Earnings Variability		

After scoring,the scores for each variable with equal weight are combined to create a combined ranking. At this point I select the top 10% and the bottom 10%. The best 10% will be the companies in which I'll have a long position, while the worst 10% are the companies in which I

short sell (a short position). I combined the long and short position, in order to exploit the quality factor and to create a portfolio that is balanced to take advantage of both rises and falls in the market. This limits the downside risk and the maximum drawdown.

Since I also would like to put in the retail investor's point of view, the first section is dedicated to the long-only portfolio because it is simpler to construct, and you don't have any liquidity or leverage constraints. In the second section, it will be presented the Long-Short construction, which is aimed at improving the factor exposures and to see whether the quality factor is consistent.

LONG ONLY PORTFOLIO

The cumulative performance for the equally weighted portfolio (P-EW) is 178% and for the cap weighted (P-CW) 155%. The two portfolios appear to outperform the benchmarks throughout the period, although until 2007 MSCI Europe did extremely well. After the Subprime Mortgage Crisis, the European Markets were also affected by the crisis and the MSCI index suffered (the maximum drawdown is 103,48%). The average annual excess returns are 7,60% for the P-EW, 8,39% for the P-CW, 0.82% for the stoxx EU and 1.74% for the MSCI index. Based purely on excess returns, the best is the cap-weighted portfolio, with an outperformance of 8,39%. On risk-adjusted returns, the top performer is the Cap Weighted portfolio with a surprisingly Sharpe Ratio of 0,66. The Cap-Weighted portfolio is able to generate the most profit, in adjusted-return terms. This is mainly related to the strong expansion, in terms of capitalization, that the market has undergone in the previous decade. It has the highest Sharpe Ratio identified, with the best average annual return of 8,73% and a relatively low standard deviation of 13,23%. In this way, the portfolio is able to grow steadily, at a relatively low-risk rate. In addition, the maximum DrawDown of 48,24% is also very significantly low. This value shows how well the portfolio reacts during turbulent market periods and how it outperforms other portfolios. On the other portfolios, the Sharpe Ratio for the P-EW is 0,63, while for the benchmark is only 0,04 and 0,08. This difference is also due to the very high volatility of the two indices with an average 20% of annualized standard deviation.

The lowest maximum DrawDown is 48,24% (P-CW), and it gives an idea of the positive management during downturns, which gives a competitive advantage when markets later recover. On the other side, the worst is the MSCI Europe (103,48%), during the Financial Crisis of 2007 and

2008. The P-EW has a maximum DrawDown of 60,59%, which is not low, meaning that the portfolio didn't react so positively during market turbulence of 2007-2008The highest Calmar Ratio is of P-CW (18,09%), as it is the best portfolio on a risk-adjusted basis during the given timeframe, while the benchmarks have a very low Calmar Ratio of 0,87% for Stoxx EU 600 and 1,68% for MSCI Europe.

In conclusion, I can say that the Long-Only Cap-Weighted Portfolio outperformed in every aspect, in terms of both risk and returns. The strong ability to bounce back after the period of severe crisis, not only in 2007-2008 but also during Covid Crisis, makes it an attractive portfolio from an investor's point of view.

	P-EW	P-CW	STOXX 600	MSCI EUROPE INDEX
Average Annual Return	7,60%	8,73%	0,82%	1,74%
Standard Deviation	12,13%	13,23%	19,56%	22,52%
Sharpe Ratio	0,63	0,66	0,04	0,08
Positive Days	54,93%	54,43%	52,23%	52,50%
Positive Months	53,85%	66,01%	56,13%	54,15%
Max DD	60,59%	48,24%	93,97%	103,48%
Calmar Ratio	12,54%	18,09%	0,87%	1,68%

LONG-SHORT PORTFOLIO

In this section, I implement a market neutral strategy, a long-short strategy, by going long those companies with the highest score and going short those companies with the lowest score. Major hedge funds use this market-neutral to deliver excess returns with lower risk by hedging long bets, considering a bull market and a price increase, with an equal number of short bets.The following portfolio is created by going long the top 10%, high-quality stocks, and by going short the worst 10%, low-quality stocks. Then, the performance is decomposed in the long side and the short side.

The cumulative returN is 131,16% for P-EW and 154,17% for the P-CW. The two portfolios outperformed against the benchmark, the Eureka Long-Short index with a cumulative performance of 125,01%. On the other side, P-EW and P-CW outperformed MSCI Europe and Stoxx Europe 600 by more than 100% in terms of cumulative performance. An interesting feature is that, during the Dotcom bubble, the long-short portfolio reacts well because of the market-

neutral strategy, as opposed to long only, see the previous section or the other two indices. Until 2003, the portfolios outperformed the benchmark with a strong positive performance and then start to decline.The financial crisis 2007-2008 is a crucial point because P-EW and P-CW reacted positively to the crisis compared to the benchmark. The Eureka growth appears to grow more stable and constant than the quality portfolios, although it is not an exponential growth.The highest average annual return is the P-CW with 7,52% for, followed by P-EW with 6,39% and Eureka Long-Short Index with 6,12%

The standard deviation is lower for P-EW than the benchmarks with 10,13%, resulting in higher result in risk-adjusted return term. Conversely P-CW has a higher standard deviation than Eurekahedge long short (14,18% instead of 11,19%). The best Sharpe ratio is 0,63 of the Equally weighted portfolios and the second is the Eureka Index with 0,55, followed by the Cap-Weighted with 0,53. The simplest weighting scheme improved on risk-adjusted returns, given the low volatility, as opposed to the Long-Only specification.The maximum DrawDown in the long-short is halved compared to the long only, giving greater robustness, with a 30% for P-EW and 46% for P-CW. Otherwise, the maximum Drawdown for Eureka Index is 48%.The return adjusted by the maximum DrawDown is 21,20% for the P-EW, the highest among the portfolios, followed by Eureka Index with 12,62%% and P-CW with 16,18%.

	P-EW	P-CW	STOXX 600	MSCI EUROPE INDEX	EUREKA L-S EUROPE
Average Annual Return	6,39%	7,52%	0,82%	1,74%	6,12%
Standard Deviation	10,13%	14,18%	19,56%	22,52%	11,19%
Sharpe Ratio	0,63	0,53	0,04	0,08	0,55
Positive Days	51,74%	51,52%	52,23%	52,50%	-
Positive Months	53,75%	52,96%	56,13%	54,15%	82,54%
Max DD	30,12%	46,46%	93,97%	103,48%	48,44%
Calmar Ratio	21,20%	16,18%	0,87%	1,68%	12,62%
Cumulative Return	131,16%	154,17%	16,12%	35,69%	125,01%

5 FACTOR FAMA & FRENCH REGRESSION

In this section, I ran this regression for the excess return of the Equally-Weighted long-short portfolio. For simplicity, I will present only the Cap-Weighted portfolio because it was the best in terms of risk-adjusted returns. It is shown the exposures to the standard factors for the equally weighted portfolio.

I ran multiple regression sequentially from the first to the fifth of the excess return, $R_t - R_t^f$, of the equally weighted long-short portfolio on the different factors. The first regression is the CAPM one with only the market factor as independent variable. The beta, associated with this factor, is higher than the cap-weighted (-0,35 instead of -0,51), reflecting the tendency of the portfolio to act as hedge against market turbulence. The annualized Jensen's alpha is 6,94%, statistically significant at 5% level. After controlling for the size factor (SMB), the market beta remains constant while the alpha is even higher. The SMB coefficient is -0,30, with a t-statistics of 3,31, meaning that the portfolio is exposed to companies with high market capitalization and tends to sell companies with small market capitalization. This evidence the characteristics of the quality factor, as shown before, to buy bigger companies than smaller, which are riskier and less safe. The portfolio is also negatively exposed to the value factor (-0,18 and a t-stat of 2,61), reflecting the inclination to buy expensive and sell cheap companies. The alpha is higher 8,26% on annual basis. When I control for the profitability factor, the alpha is almost halved meaning that RMW factor explains part of the performance and therefore the alpha is smaller. The RMW is 0,63 and a t-statistics of 4,83. As a result the portfolio tends to buy profitable companies and sell unprofitable one. The investment factor is positive (0,61) and statistically significant at 5% level, showing that it prefers to invest in safer stock with low level of investment.

In conclusion, the results are robust with the definition of quality factor made by the literature

TABLE 1

Equally Weighted Portfolio, 6/2000-5/2021 (t-statistic in parentheses)						
Alpha*	**6,94**	**7,70**	**8,26**	**4,83**	4,04	
	(3,12)	(3,51)	(3,79)	(2,19)	(1,89)	
Mkt-RF	**-0,35**	**-0,35**	**-0,33**	**-0,27**	**-0,19**	
	(10,17)	(10,31)	(9,40)	(7,75)	(4,77)	
SMB		**-0,30**	**-0,31**	**-0,30**	**-0,23**	
		(3,31)	(3,44)	(3,51)	(2,75)	
HML			**-0,18**	-0,01	**-0,31**	
			(2,61)	(0,11)	(3,10)	
RMW				**0,63**	**0,58**	
				(4,83)	(4,60)	
CMA					**0,61**	
					(4,47)	
R Square	0,55	0,57	0,59	0,63	0,67	
Obs.	252	252	252	252	252	
*Alphas are annualized. Boldface indicates statistical significance at the 5% level						

In this section, it is carried out the univariate portfolio analysis sorting by quality factor. The quality factor is built using the same criteria as the portfolios, illustrated above.
The variables are: Gross Profit-to-Total Assets, ROA, Operating Cash Flow-to-Debt, Debt-to-Equity and YoY Earnings Variability

The table shows the results of two different analyses using two different weighting schemes: value-weighted and equally weighted.

There is the linear relationship between quality factor and future stock returns. the relationship is statistically significant and positive. Panel A shows an average Cap weighted return of 5,97% per year, with a T-statistics of 5,44, meaning that is statistically significant at 99% level. In Panel B, the average excess return is 5,05% per year (t-statistics of 6,41), statistically significant at 99% level. The returns are increasing monotonically from low-Quality portfolio to high-Quality portfolio, except for the second portfolio (80th percentile).

Panel A: Value Weighted Portfolio Returns sorting by Quality

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	1,39	2,15	3,88	4,03	4,61	7,36	5,97
T-Stat	1,92	1,84	2,68	3,06	2,80	4,47	5,44

Panel B: Equally Weighted Portfolio Returns sorting by Quality

Percentile	*10*	*20*	*40*	*60*	*80*	*90*	*90-10*
Average	3,37	5,88	6,38	6,44	7,66	8,42	5,05
T-Stat	2,29	3,99	4,42	5,41	5,75	6,29	6,41

CONCLUSION

The thesis uses the Sharpe Ratio as the main indicator for risk-adjusted performance. All the quality portfolios have positive Sharpe Ratio and greater than benchmark portfolios. The best performing portfolio is the Long-Only Cap Weighted with a Sharpe Ratio of 0,66, followed by the Long-Only Equally Weighted with 0,63. Using a market neutral strategy, the Sharpe Ratio are lower but still greater than the benchmark 0,627 (Equally Weighted Long-Short and 0,53 (Cap Weighted Long short).

This thesis uses Fama-French five factor model as the main asset pricing model. All the strategies produce significant and positive Alphas. Additionally, a robustness check is made, using monthly and daily data. The results are robust and consistent, producing both significant Alphas. Moreover, the significant loadings are mainly on profitability and investment factor, meaning that the portfolios tend to buy profitable and conservative firms and to sell short unprofitable and aggressive firms.

This research thesis is aimed at discovering a new factor to generate positive alpha in the long-short strategy. As far as the author of this thesis was aware, no previous studies regarding the test of a new factor through quantitative analysis in the European market had been conducted. The anomaly generated by quality portfolios can be explained from two different points of view: the risk-based view and the behavioural view. The former is in line with the efficient market hypothesis and states that the abnormal excess returns, generated by the long-short strategy, is the compensation for risk, which is to say that investing in quality firms is riskier. The latter states that investors are not rational and undervalue the high-quality firms. This view contradicts efficient market hypothesis.

Capital Fund Management and CFM-Imperial Institute of Quantitative Finance[5] found that is hard to account for this anomaly using a risk premium argument, which are characterized by a negative skewness and a propensity to crash, while returns of quality strategies have all positive skewness. By contrast there is evidence that investors don't pay attention to firm-level profitability such as cash flow to assets. This behavioural bias could be because analysts are too focused on other indicators such as EPS, Book-to-Market, Momentum and volatility. Additionally, people and investors form biased beliefs and tend to overestimate the quality of the private information, while don't consider properly public information. Because of this biased behaviour, stock prices might take time to adjust reflecting the true value of the companies. Eventually, investors systematically underestimate future earnings growth and returns of high-quality firms, compared to low quality.

[5] Jean-Philippe Bouchaud , Stefano Ciliberti , Augustin Landier , Guillaume Simon, and David Thesmar, "The Excess Returns of Quality Stocks: A Behavioral Anomaly", 2016.