A Work Project, presented as a part of the requirements for the Award of a Master's Degree in Finance from Nova School of Business and Economics

Decoding the Quality Factor

Nova SBE Consulting Project for BPI GA

Carolina Domingues, 31951

Laura Meneses, 32222

Lorenz Ambrosius, 44155

Mariana Branco, 32360

Pascal Linz, 45110

Work project carried out under the supervision of:

Professor Giorgio Ottonello

December 17, 2021

Abstract

This paper aims to improve the understanding of the Quality Factor and test whether BPI GA's proprietary quality strategy can be improved through extension to other dimensions. By running a regression analysis for BPI Opportunities fund and extending its strategy to other dimensions, it was documented that (1) BPI Opportunities exhibits exposure to quality; (2) a bottom-up approach combining quality and value investing is not beneficial in the current market environment; (3) a long-short strategy creates value; (4) applying an ESG calibration improves the portfolio's ESG rating without compromising risk-adjusted returns. Furthermore, the performance of the quality premium under different macroeconomic environments was tested. The results suggest that its performance is superior during market downturns (phenomenon defined in literature as "flight to quality"), while being hampered in times of economic growth.

Keywords: Asset Management; Factor Investing; Quality Investing; ESG Integration.

Acknowledgments

We would like to express our sincere gratitude to our business advisors, Professor Jorge Sousa Teixeira, João Abrantes, Luís Alvarenga and Rui Araújo, for their support, insightful feedback, and engaging discussions throughout the completion of this project. We are also thankful to the entire BPI GA team for their warm welcome and collaboration. Last but not least, we are extremely grateful to our supervisor, Professor Giorgio Ottonello, for the valuable recommendations, feedback, and guidance. Thank you all for challenging and inspiring us, contributing greatly to the completion of the present MSc Thesis and to our professional growth.

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Table of Contents

Table of Exhibits

Table of Annexes

List of Abbreviations

AuM – Assets under Management

APT – Arbitrage Pricing Theory

CAPM – Capital Asset Pricing Model

CI – Confidence Interval

CMA – Conservative Minus Aggressive

D/E – Debt-to-Equity Ratio

EPS – Earnings per share

EBITDA – Earnings Before Interest, Taxes, Depreciation and Amortization

ERP – Equity Risk Premium

ESG – Environmental, Social and Governance

HML – High Minus Low

MOM – Momentum

MPT – Modern Portfolio Theory

MRP or MKT-RF – Market Risk Premium

OCF – Operating cash flows

OLS – Ordinary Least Squares

Pp – Percentage Points

QMJ – Quality Minus Junk

RMW – Robust Minus Weak

ROA – Return on Assets

ROE – Return on Equity

ROIC – Return on Invested Capital

SMB – Small Minus Big

1. Introduction

"It's far better to buy a wonderful company at a fair price than a fair company at a wonderful price" ~ Warren Buffett (Buffett, 1989)

Warren Buffett, the world-famous investor and chairman of Berkshire Hathaway, understood the value of quality before its premium was empirically proven. Investors preference for stocks with value, quality, or other characteristics dates back centuries. However, only with the emergence of the arbitrage pricing theory, investors were provided with the theoretical principles needed to develop a more systematic approach of seeking style premia. Thus, leveraging on the APT, factor investing, an investment strategy that systematically exploits style premia, was developed. Witnessing significant inflows, Blackrock projects the factor investing industry's assets under management to grow from $1.9 trillion in 2017 to $3.4 trillion by 2022 (BlackRock, 2021).

Evidence suggesting that quality investing can be improved by extending it with other styles and dimensions was found reviewing the literature. Research by Novy-Marx (2014) argues that a combination of quality and value investing delivers improved risk-adjusted returns, Novy-Marx (2012) suggests that results of long-short quality portfolios outperform long-only portfolios and Melas et al. (2016) find that high-quality companies tend to have above-average ESG ratings. However, none of these findings have been analysed from the perspective of an institutional investor.

This paper aims to provide evidence on BPI GA's quality portfolio's exposure to the quality factor and improve the firm's proprietary quality model. BPI GA is a leader asset manager in Portugal and offers a range of quality-centered products. The firm's focus on quality investing makes it susceptible to changes in returns associated with the quality premium. Hence, this paper starts by examining the exposure of BPI GA's quality strategy to the quality factor and investigating the performance of the quality premium in various macroeconomic environments. This paper develops different analyses to (1) validate the Bloomberg factors used by BPI GA for factor analysis, (2) prove BPI GA's quality strategy's exposure to the proxies selected for quality, (3) test whether extending BPI GA's strategy to other dimensions can create value.

This dissertation introduces the existing literature, relevant theory, and BPI GA in the first part. Second, it goes over the data and methodology used and conducts a robustness test on the three factor models. Thirdly, it assesses BPI Opportunities exposure to the quality factor. Fourthly, the effect of different macroeconomic environments on the quality premium is investigated. Fifthly, the extension of BPI GA's quality strategy with various other dimensions is tested. Finally, conclusions are drawn, and limitations and further research are indicated.

2. Literature Review

2.1 Factor Models

Factor models estimate asset returns through their relationship with certain factors and the market. One of the main research goals in finance is to enhance the understanding of stock price behavior by exploring its main drivers and the associated returns. The modern portfolio theory (MPT) developed by Markowitz (1952) is an example of a model that attempts to explain assets returns by analysing the underlying risks of securities. It suggests that specific risk associated with a stock can be diversified away, being that investors should only be compensated for bearing systematic risk.

Arising from this discovery, researchers have attempted to determine the systematic risk factors that affect share prices. The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965), and Black (1972) marked the birth of security pricing and has long shaped how academia and practitioners think about returns and risk (Fama and French, 1992).

Basing the model on the MPT, the CAPM assumes that investment portfolios are mean-variance efficient. It divides the expected return of a security into a risk-free rate component plus a risk premium associated with the exposure of a security to the systematic risk of the market, denominated as β. Thus, the CAPM is an ex-ante model relying exclusively on systematic risk, to determine future returns of an asset. It relates the expected return of an asset to its risk that can be decomposed into a systematic and idiosyncratic component. Systematic risk is contingent on the market as a whole and cannot be diversified, while idiosyncratic risk is specific to security and can be fully diversified away.

Furthermore, the efficiency of the market portfolio implies that an asset's expected return is a linear equation of its systematic risk (β) and that markets suffice to describe cross-sectional expected returns. The CAPM formula is given by:

$$\text{(1)}\ E[r_i] = R_f + \beta(R_M - R_f)$$

$$\text{(2)}\ \beta = \frac{Cov\,(R_i, R_M)}{Var\,(R_M)}$$

where $E[r_i]$ is the expected return on assets, R_f corresponds to the return on risk-free investments, R_M is the return of the market and β corresponds to a measure of systematic risk (Fama and French, 1992) (Hull, 2012).

Conceptually building on the CAPM – suspecting that one factor may not suffice to describe a security's return – Ross (1976) developed the Arbitrage Pricing Theory (APT). Similar to the CAPM, the APT predicts a firm's expected returns based on market risk factors. However, the APT is a multifactor asset pricing model, incorporating numerous firm-specific macro indicators in an attempt to optimally explain a firm's systematic risk, and forecast its expected returns.

All things considered, factors can be thought of as "any characteristic relating to a group of securities that is important in explaining their returns and risk" (Bender, J. and Briand, J., 2013) that are persistent throughout time. The model implies that an asset's return can be broken down into an expected and an unexpected component, where the unexpected component of an individual stock can be divided into a systematic part that affects all stocks at varying levels and a stock-specific component. Thus, the APT is more inclusive than the CAPM, allowing for a larger number of asset pricing factors to affect the expected rate of return of a given security. Furthermore, it is worth noting that APT does not propose specific factors, however, it does provide the theoretical basis for future multifactor models. The APT is given by:

$$(3)\quad E(r_i) = R_f + \beta_{i1}F_1 + \beta_{i2}F_2 \dots + \beta_{ik}F_k + \epsilon_i$$

Where $E(r_i)$ is the expected return of the asset, R_f corresponds to the risk-free rate, β_i to the sensitivity of a security to a macroeconomic factor and F_i constitutes the risk premium of factor i (Bodie, Marcus, and Kane, 2014).

Following the creation of CAPM, several researchers have found that realized returns of stocks with certain characteristics deviate from the expected returns computed using the CAPM. Most notably Banz (1981) found that small firms had higher risk-adjusted average returns than large firms over a forty-year period. These higher returns could not be explained through market exposure and suggested misspecification of the CAPM (Banz, 1981). Additionally, Basu (1983) found empirical evidence suggesting that stocks with high earnings yield had higher returns than what was predicted by CAPM (Basu, 1983). Thus, ample research provides evidence that the CAPM fails to explain the cross-sectional variance of stock returns and omits relevant factors explaining expected returns.

Encouraged by the empirical failures of CAPM and the discovery of APT, Fama and French (1992) developed the Fama-French three factor model to better explain the cross-section of stock returns. The Fama-French three factor model argues that a security's expected return can be explained through the systematic risk factors market, size, and the book-to-market ratio. In line with previous research, Fama and French confirm that a simple relationship between the market beta and return is weak between 1941 and 1990, while it disappears entirely between 1963 and 1990.

Following Banz (1981) discovery of strong negative relationships between a firm's size and return, Fama and French introduced the factor Small minus Big (SMB) intending to capture the systematic factor size. Equally, Fama and French, drawing on research by Basu (1983) and many more suggesting the existence of a value premium, introduced the value factor High minus Low (HML) (Fama and French, 1992). Hence Fama and French included the systematic factors market, size and value to capture additional systematic risk otherwise omitted by the CAPM in their three-factor model (Bodie, Marcus, and Kane 2014). After controlling for these two factors, the relationship between stock returns and market beta became much weaker (Fama and French, 1992). Following the success of Fama and French, Carhart (1997) extended the model with a fourth factor, adding the factor momentum, explaining the average return difference between well performing and poor performing securities. Finally, Fama and French (2015) extended the model, introducing the factors profitability and degree of investment to the Fama-French three factor model. The main rationale for the increased explanatory power of both Fama-French and Carhart models is that factors related to momentum, size, profitability, degree of investment and book-to-market are proxies for additional risk factors that are omitted by the CAPM and the Fama-French three factor model (Hanauer and München, 2014).

The Fama-French three factor model is a contemporary model heavily relied upon by practitioners and given by:

$$(4) \quad R_{it} - R_{ft} = \alpha_{it} + \beta_1(R_{Mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{it}$$

Where $R_{it} - R_{ft}$ *is the expected excess return,* α_{it} *corresponds to the fraction of the return that is not explained by the factor coefficients,* R_{Mt} *is the return of the market portfolio,* R_{ft} *corresponds to the risk-free rate of return,* SMB_t *is the size premium,* HML_t *is the value premium and* $\beta_{1,2,3}$ *are the factor coefficients.*

Beyond establishing the three-factor model, Fama and French introduced a methodology to create factor portfolios and measure risk premium. Like the APT, Fama and French constructed zero net investment portfolios by going long on value/small companies, while shorting growth/large companies (Bodie, Marcus, and Kane, 2014).

To conclude, even though CAPM is a great starting point for asset pricing, it can be improved by including other risk proxies that are not perfectly correlated with the market returns and that represent other sources of non-diversifiable risk, to which returns are sensitive. This is achieved by the creation of different multifactor models explained above.

2.2 Factor Investing

Factor investing is an investment strategy that is aimed at systematically exploiting factor premia that have proven to be robust over time and in different markets. As investors increasingly perceive portfolios as a collection of factor exposures rather than a collection of individual stocks, the investment strategy is gaining significant traction with prominent investors. This is illustrated by significant growth in assets under management from USD 1.9 trillion in 2018 to an estimated USD 3.4 trillion by 2022 (BlackRock, 2018). Thus, factor investing, also referred to as smart beta investing, is targeting factor premia to generate returns.

2.3 Introduction to Quality

The following section will define quality, explain the quality anomaly and review relevant literature related to the aforementioned.

2.3.1 Defining quality attributes

Quality companies are defined by various profitability and capital structure indicators. However, no standard definition has been agreed on so far – this explains why the investment community uses different metrics to define quality (*Annex 1*). The variety of ways in which quality has been defined, differ in complexity, ranging from one-dimensional metrics to multi-dimensional metrics that compile a set of quality characteristics. All one-dimensional measures are grouped in seven main categories (Hsu, Kalesnik, and Kose, 2019):

- **Profitability** (Gross Margin, ROA, ROE, ROIC)
- **Growth in Profitability** (Long-term change in ROE, Long-term change in ROA)
- **Earnings Stability** (Stability of EPS Growth, of Gross Margin, of Cashflow Profitability)
- **Accounting Quality** (Accruals, Net operating assets)
- **Capital Structure** (Total leverage, D/E, Financial leverage)
- **Payout/Dilution** (Net payout, debt issuance, equity issuance)
- **Investment** (Growth in total assets)

To determine the best quality attributes, Hsu, Kalesnik and Kose (2019) ran three types of robustness tests for each quality attribute:

1. *Average portfolio return difference*: tests whether a high-quality portfolio outperforms a low-quality portfolio
2. *4-Factor model alpha*: tests whether alpha is significant under the context of a 4-factor model if it is sufficiently negatively correlated with other factors.

3. *Sharpe ratio*: tests whether the Sharpe ratio of a high-quality portfolio is significantly higher than the one of a low-quality portfolio.

The tests led to the conclusion that profitability as a factor, generates superior performance on a multifactor basis, and is robust. This also holds for metrics on payout/dilution, accounting quality and investment. The paper claims that the combination of investment and profitability signals make up the quality definition associated with the strongest scientific evidence on delivering superior performance. Conversely, average capital structure, earnings stability and profitability growth metrics fail to prove their robustness.

These findings are in line with previous research. Novy-Marx (2013) advocates the use of profitability, defined by the gross profit – the purest measurement of profitability according to the author – as a proxy for the quality factor due to its strong predictive power. AQR Capital Management has extended the research of Novy-Marx to incorporate free cash flow over assets, profits over assets and gross margins, to create a multidimensional quality definition. Other combinations of profitability metrics have also proved to deliver significant excess returns.

Asness et al. (2014) have shown that sorting portfolios based on profitability – measured by a composite z-score that captures gross profits over assets, gross margin, accruals, ROA, ROE and cash flows to assets – have produced statistically significant alphas globally (Norges Bank, 2015).

All in all, these strategies are in line with the findings of Hsu, Kalesnik and Kose (2019), suggesting that a combination of different profitability and investment attributes identify quality companies with superior returns.

2.3.2 Quality as an anomaly

The quality anomaly is one of the most well documented anomalies in the market. By ranking firms in terms of a quality indicator – operating cash-flow, debt-to-equity, ROA, etc. –

investors can build a portfolio that is long high-quality stocks and short low-quality while pocketing high profits. Since this investment strategy is based on indicators that are public and easy to process, the persistence of the quality anomaly lacks a clear explanation. As market anomalies tend to vanish when they are arbitraged, the question of whether the factor excess returns will persist in the future, begs to be answered. Attempting to explain the existence of the quality anomaly, a relatively recent study offered two explanations on this: a risk-based view and a behavioral view (Bouchaud et al. 2016).

The risk view, consistent with the Efficient Market Hypothesis, states that investing in high-quality firms is riskier, meaning that higher returns of a quality portfolio are a compensation for a source of risk. The rationale behind this is that firms can undertake two types of corporate investments: risky or safe. Risky projects are more profitable, providing high OCF/Assets figures as they operate in more profitable, yet riskier segments of the market. On the other hand, safer projects are moderately profitable, produce lower OCF/Assets ratios, and are associated with safer segments of the economy.

This view is challenged by one of the pillars of modern finance – risk premia – meant to compensate investors for carrying negative skewness risk (Lempérière et al. 2017). The issue stems from the fact that quality strategies seem to have positive skewness and a small propensity to crash (Bouchaud et al. 2016), which makes the existence of a quality risk premium very unlikely, as investors shall not be compensated for carrying positive skewness.

A more plausible explanation for quality is the behavioral view, inconsistent with the Efficient Market Hypothesis. This explanation is based on the fact that investors might be systematically underweighting the information that quality-like signals contain (ROA, cash-flows, etc). The two pillars of the behavioral view are misplaced focus and conservatism bias. The first one has to do with the excessive focus that investors have on indicators such as earnings per share and volatility, failing to use other indicators such as ROA, which is based on relevant information contained in the financial statements. The second one, states that investors' beliefs are sticky, leading to under-reaction to any sort of news about firms. As investors focus heavily on salient information (Griffin, Tversky, and Negotiation 1993) while neglecting other relevant sources of performance information, stock prices take more time to fully reflect the existing information on companies. All in all, analysts tend to make fewer mistakes on high-quality firms when forecasting returns, showing that they are more optimistic about low-quality firms (*i.e.,* growth stocks and high volatility stocks). These results suggest that this anomaly has a behavioral nature and exposes the main question that everyone should be asking: "How long will investors remain inattentive and sticky to their beliefs in an era that is dominated by computerized data analysis?" (Bouchaud et al. 2016).

Additionally, González-Urteaga and Rubio (2021) provide a market friction-based explanation for the striking performance of the quality factor. They provide evidence that the quality premium is, at least, partially explained by leverage constraints in the form of margin requirements, accompanied by funding illiquidity. Leverage and liquidity constraints result in a flatter empirically implemented CAPM, the intercept of the security market line is positive and significantly related to margin requirements, while the slope is negative and significantly related to margins. Alphas tend to be higher in low funding liquidity and high tightness times. The paper does not deny the behavioral view but rather provides additional evidence to understand the outperformance of quality (González-Urteaga and Rubio 2021). Frazzini and Pedersen (2014) also highlighted that constrained investors – who cannot access leverage – tend to allocate their funds to higher beta assets in order to boost the portfolio's overall market exposure. This structural issue ends up leading to lower adjusted returns from higher beta assets, which in turn gives rise to the quality premium.

2.3.3 Quality investing

Quality investing is based on the idea that firms that have a sustainable competitive advantage, strong balance sheets, durable business models, stable earnings, and low financial leverage outperform the market average return in the long term. Thus, the strategy aims at capturing the return of high-quality companies in excess of the market. Many investors consider this equity investing style a complement to other investment styles and, eventually, an additional risk factor to be added to small-cap, momentum, and value factors.

The following adds to the introduction of the quality anomaly. Despite the economic significance of quality investing, little research has tried to explain the quality premium (Norges Bank, 2015). Asness, Frazzini, and Pedersen (2019) have pointed out the fact that investors should be willing to pay a higher price for quality companies as they typically generate higher expected cash-flows, *ceteris paribus*. Theoretically, quality should command higher prices and not necessarily higher risk-adjusted returns – nevertheless, empirical evidence shows that this factor might not be completely priced in the cross-section and, therefore, quality seems to generate excess returns.

Counterintuitively to the state-of-the-art asset pricing models – which suggest that higher returns come at the cost of higher risk – high-quality companies have been associated with lower risk levels. While size and value risk premia serve as compensation for the illiquidity and distressed risks inherent in smaller and cheaper stocks, what risks are we incurring when holding high-quality stocks? The answer could be hidden in the core assumptions of *e.g.,* the CAPM. It is erroneous to assume that all investors have a risk-averse posture. If we consider a heterogeneous risk appetite among investors, consisting of risk-averse and risk-seeking investors, one could establish a line of reasoning: if risk-averse investors are the ones who hold quality stocks in the pursuit of certainty in investment outcomes, risk seekers are the ones responsible for bidding up the price of low-quality stocks, "to the point that they are bound to underperform" (Northern Trust, 2013). This could explain why quality stocks (lower volatility) are underpriced relative to junk stocks (high volatility), being that the risk-seeking goal is to capture the large upside potential, even in a volatile market environment.

Despite this explanation, the quality premium could be due to a variety of factors – measurement errors, inappropriate models, behavioral biases, statistical errors, and institutional constraints – and its size is bound to differ across time periods, geographies, and asset pricing model.

2.3.4 Identifying future quality companies

The quality of management and balance sheet are the most promising indicators of future quality companies. While the ability to identify the next Apple would be equivalent to finding the holy grail, research suggests that certain company characteristics may help identify future quality companies. Nikko Asset Management defines future quality as a firm that can generate sustainable cash flow growth as well as high and improving returns on the capital invested (Kinghorn, 2018).

The main pillars of the art of finding future quality are the quality of management (strategic capital allocation), the quality of the balance sheet (appropriately financed growth), the quality of the franchise (sustainable competitive advantage) and a disciplined valuation (disciplined approach). Typically, firms create value by creating a spread between their CROIC (cash-return on invested capital) and their cost of capital. Nevertheless, knowing for how long this gap might be sustained is pivotal in determining the competitive advantage period of a company, as the future quality of a company depends on the forecast for the sustainability of this spread and the ability of the firm to reinvest the excess returns into the business. Thus, investors should focus on companies that improve their various profitability indicators and maintain their competitive advantage (Fruhan, 1979). Understanding the capital intensity of the business and its business model allows for deep comprehension of the quality of franchise, which helps investors make an informed assumption on the profitability, growth rate and competitive advantage period of the underlying business. The quality of management is of paramount importance to determine whether the capital allocation decisions will harm the competitive advantage, as well as if they ensure the sustainability of the return spread.

Lastly, the quality of the balance sheet will provide an insight into the company's funding sources and the cost of that funding, while the quality of valuation aims at guaranteeing a fair valuation. All these pillars are key components to compute future CROIC and the firm value, allowing investors to assess a company's future quality.

2.4 Quality – Macroeconomic and Sectoral perspective

In the following section, literature covering the performance of quality and its premium under different macroeconomic environments and across different sectors will be reviewed.

2.4.1 Quality under different macroeconomic environments

Quality outperforms the market regardless of GDP development. Ung et al. conducted a study on the performance of the quality factor on different macroeconomic environments by comparing the return profile of the S&P Quality Index with that of the S&P 500 in different periods of economic growth (measured by the real GDP growth) using data from December 1994 to December 2013 (Ung, Luk, and Kang, 2014). Their analysis indicates that, even though quality stocks always outperform independently of how GDP evolves, the magnitude of the outperformance is sensitive to economic development. In periods of below-average real GDP growth (current growth below 5-year average), significant excess returns of the quality stocks can be observed compared to the S&P 500. Even with above-average real GDP growth (current growth above 5-year average), the S&P Quality Index exhibits excess returns – though less significantly than in below-average growth periods.

Additionally, the *flight to quality* phenomenon, which dictates that quality provides higher excess returns during market downturns, is hereby explained. Gupta et al. (Gupta et al. 2014) conducted a study where they combined the economic growth factor with inflation to examine the performance of the quality factor in more detail. The study results confirmed that quality shows the strongest outperformance during a real GDP growth slowdown, regardless of whether inflation is rising or falling. However, a distinction can be made in the environment of rising (above average trend) real GDP growth. In combination with rising inflation, quality stocks show a moderate outperformance, whereas in combination with falling inflation a moderate underperformance can be observed. This behavior can be explained by the characteristics of a quality company. Competitive advantage, cash flow consistency, and pricing power (typical attributes of quality companies) can dampen the negative impact of inflation relative to other businesses without those attributes (Jensen Investment Management, 2021). Asness et al. (2019) provide evidence that during (extreme) down market phases the quality premium (Quality-minus-Junk) showed solid excess returns. This occurrence is also known as "flight to quality" (Asness et al., 2019). This phenomenon may be explained by the fact that investors are willing to pay a higher price for quality stocks during strong market downturns as they are trying to cope with market uncertainty. According to Hunstad, M. (2013) this can be attributed to the inconsistency of investors' risk affinity as they change their risk appetite in response to market conditions. Consequently, the number of risk-seeking investors decreases during depressed market periods and vice versa. Therefore, a portfolio of high-quality stocks is expected to perform very well during periods of market downturn.

Analysis of VIX and quality in rapid market downturns suggests stellar performance in such environment. The volatility of the market and particularly rapid market downturns can be analysed by looking at spikes in the VIX (CBOE Volatility Index). Ung, Luk, and Kang (2014) noted that the outperformance of the S&P Quality Index was most pronounced when investor sentiment was bearish, *i.e.*, when the VIX was strongly above average. It is worth noting, that marginal outperformance of the S&P Quality Index was also achieved in bullish or neutral markets, but not to the same extent and consistency as in bear markets. This is in line with the thesis that a flight to quality takes place in down-market periods.

2.4.2 Sector bias of the quality factor

The importance of sector specific quality returns is increasing. It is important to examine the quality factor independent of the macroeconomic environment to assess sector-dependent effects. Baca et al. (2000) have already shown that industry-specific effects on equity return variance have been increasing since the early 1990s relative to country-specific effects. They explain this by the increasing globalization and interconnection of capital markets (Baca, Garbe, and Weiss 2000). Similar results were also obtained by Cheng et al. (2006). However, they argue that the reason for this is not the decreasing importance of the country effect on the equity return variance, but the rapidly growing technology and telecommunications industry (Chen, Bennett, and Zheng 2006). This illustrates the increasing importance of industry effects in analysing factor investment strategies.

Ung et al. (2014) were able to show a certain sector bias of the quality factor by analysing the composition of the S&P Global Quality Index over the period from 1999 to 2013. The results indicate that across different periods, there is a noticeable bias towards healthcare, information technology, energy, and consumer staples. Over the entire period, there is only slight exposure to Utilities and Telecommunication Services. Their examination of this data with respect to sector bias showed that, while sector bias contributes to outperformance, it is not the sole driver of the excess returns and that the results over the entire period did not show consistent outperformance due to sector bias (Ung, Luk, and Kang 2014). Vyas & van Baren (2020) argue that there is substantial homogeneity in stock characteristics for stocks in the same industry, meaning that if an investment decision is based on predetermined factors (such as quality) without considering the sector differences, the factor investing strategy becomes an industry bet.

2.5 Combining Quality with other Risk Factors

The fervor for factor investing continues to grow, and so do the combining factor approaches that seek to benefit from multiple pricing anomalies simultaneous in one single product. The number of multifactor funds, as well as the assets invested in multifactor funds, has been growing significantly over the past decade, signaling that the market is maturing (Bryan, A. et al. 2020). The advantages of multifactor models are documented in the literature. Research by Clarke, de Silva, and Thorley showed that factor portfolios that blend multiple factors were less volatile and more consistent, indicating a better performance over the long term. The strategy can also offer diversification benefits but finding the right combination is crucial to ensure outperformance (Clarke, Silva, & Thorley, 2016).

Correlation among factors is often strongly negative, as it is generally the case with the quality and value factors. Therefore, multifactor strategies stand the risk of being factor neutral. Investors should control for the low-quality orientation of the value strategy and vice versa to avoid unintentional offsetting of factor exposures. As pointed out by Michael Hunstad, the dilution effect may result in multifactor products with little or no net factor exposure, essentially resulting in an index-like strategy (Hunstad, 2020).

Attempting to find the best performing factor combination, a list with the most promising combinations of factors can be found below.

2.5.1 Combining quality with value

In terms of philosophy, these two strategies are quite similar. "Buying high-quality assets without paying premium prices is just as much value investing as buying average quality assets at a discount" (Novy-Marx, 2013). Nonetheless, in terms of holdings, the strategies tend to be particularly different. The essence of quality investing is buying good businesses, therefore quality firms tend to be expensive. On the opposite side, value firms tend to be low-quality, enjoy the discount of undervalued stocks.

Novy-Marx in the paper ‘Quality investing’ studied the correlation between seven different definitions of quality and value. Quality exhibit a negative correlation with value: quality tends to perform best when value suffers large drawdowns, and vice versa. Therefore, combining both signals can generate steadier returns. The researcher concludes that quality explores another dimension of value by helping traditional value investors distinguish undervaluation from “value traps”. Combining a long-only quality with value (in the form of book to price ratio) through an integrated approach produced returns with a better risk-reward ratio than stand-alone strategies of quality, except for two strategies: earnings quality and defensive equity strategy. Sedeek and Elgiziry (2020) reinforce this argument. According to the literature, the combination of quality and value either by applying an equal-weighted strategy or by imposing a quality strategy in a value universe lead to outperformance and lower volatility compared to the value index (Ung, Luk, and Kang, 2014).

2.5.2 Combining quality with dividend yield

A high dividend yield strategy can capture higher yield coming from either lower-priced securities or from companies that pay more of its earnings as dividends and therefore show a higher payout ratio (Reddy, 2019). Adding a quality factor may potentially reduce the risk of falling into a dividend trap. Backing this hypothesis, the literature shows that the factor combo outperformed the two strategies separately in all market environments (S&P Dow Jones Indices, 2019).

2.5.3 *Combining quality with low volatility*

Since quality companies are usually stable and profitable, intuitively they should be less volatile than low-quality companies. Therefore, it is expected that these two factors have a high correlation. Confirming this suspicion, Ung, Luk, and Kang (2014) prove a strong correlation between the two factors. Nevertheless, the two strategies are quite different. While low volatility can be seen as one of multiple metrics used to define quality, quality and low volatility are two defensive strategies. Hence, combining these two strategies significantly decreases the volatility of the portfolio as shown by a Northern Trust paper (Northern Trust Asset Management, 2014).

2.5.4 *The importance of size in quality investing*

Benjamin Graham, a pioneer of the value investing approach, already understood the importance of adequate company size as a criterion for a quality company (Graham,1959). The systematic risk associated with small capitalization companies is the source of the factor return size. There are different explanations why small companies often offer a higher risk premium, a discovery that dates back to Banz (1981). On one hand, Dichev (1998) argues that smaller firms have a higher chance of falling into distress, while Liu (2006) attributes the risk premium to lower liquidity. According to Zhang (2006), the risk premium could also be based on the lower transparency of small firms. Asness et al. (2018) examined the relation of the size factor and quality factor in their paper "Size Matters, If You Control Your Junk”. Controlling small companies for junk, a much stronger and more stable size premium emerges that is robust across time. These results are also robust for various quality measures.

Regarding the impact of the size on the quality factor, there is a size bias well known by practitioners – quality firms tend to be big companies. Robert Novy-Marx studied seven different definitions of quality and all of them showed strong size biases (Novy-Marx, 2012). There is a strong negative relation between size premium and quality, holding for every industry

(Asness et al. 2018). This tilt towards large-cap companies raises concerns about the predicting performance within a given universe as pointed out by Novy-Marx. Nevertheless, the results show significant excess returns in both the small and large-cap universe. Asness et al. (2018) also found that the largest firms are tilted to quality, while small firms tend to be "junky". The results of the study show an increase in returns when controlling for firm size, confirming the robustness of the quality premium.

2.5.5 Top-down and bottom-up approach factor investing strategies

The top-down approach is defined as an investing strategy that identifies stocks with certain factor exposure (*e.g.*, quality or value) to construct a given number of style portfolios, in a first step. Second, it combines these separate portfolios in a new portfolio using any given proportion (*e.g.*, weighing the quality index at 40% and value at 60%). Using individual factors as building blocks provides ample advantages such as higher flexibility, higher capacity, and lower tracking error (Kulkarni, Gupta, and Doole 2018). However, its disadvantages outweigh as these strategies fail to consider how the factors come together in a portfolio. Combining different factors can lead to the loss of exposure of all anomalies that the strategy is trying to capture, hence, ending up delivering no alpha. An example of such phenomena is the top-down combination of value and quality portfolios, which can lead to the loss of both factor exposures, as the factor exposure of the two strategies is inversely correlated.

In a bottom-up approach, all factor characteristics are considered simultaneously (FTSE Russell, 2018). Bottom-up indices target specific factor exposure and avoid unintended factor tilts, solving the above-mentioned issues (Kulkarni, Gupta, and Doole 2018). This approach tends to overweight stocks with multiple positive exposures, and it is more complex, as it requires evaluating each security individually. While this strategy is likely to result in a more selective, concentrated portfolio of stocks, it is also more efficient and solves the neutralization problem (Ang, A. and Framsted, H.). An example of a bottom-up strategy could be an approach, where stocks with high-quality exposure are identified in a first step. Second, securities with the poorest value characteristics are being excluded from the strategy. Evidence that such strategy yields superior risk-adjusted returns is provided in a study by Kulkarni, Gupta, and Doole (2018), finding that the bottom-up approach delivered higher annualized returns, Sharpe ratio and Information ratio than the top-down approach. Equally, a Northern Trust study finds the benefits of intersection over a linear combination of single factors. For all factor pairs studied (quality-value, quality-small size, quality-low volatility, and quality-dividend yield) the return of the intersection portfolio significantly exceeds the return of the linear combination portfolio, while the standard deviation of both strategies is roughly equal. For the volatility and dividend yield, it is even significantly lower (Northern Trust Asset Management, 2014).

2.6 Long-Only and Long-Short Strategies in Quality Investing

Academic research tends to focus on long-short strategies as it allows for a simple and understandable analysis of the quality factor premium. Assessing the difference in annualized excess returns between long-only and long-short strategies, one can find that long-short strategies outperform long-only strategies across different regions and periods (Novy-Marx, 2012).

These findings are aligned with academic research that suggests that leverage allows unconstrained investors to pursue opportunities that provide the highest risk-reward ratio regardless of the absolute risk level. Institutional investors, however, are typically limited to long-only strategies as they are constrained by their mandate, tracking error and high costs of implementing such strategy (Lepetit et al. 2021). Having to consider risk and reward jointly, they may rationally choose to pass on an investment with a higher risk-reward trade-off for another investment more in line with the funds' risk profile.

Another issue arising from long-short investment strategies for institutional investors is market neutrality. Long-short quality investing strategies tested by Lepetit et al. (2021) exhibit either insignificant or very close to zero market betas, across different geographies in the period from 2003 to 2020. This poses a problem for many institutional investors as it impairs absolute returns and their ability to perform in line with the market plus a single-digit tracking error (Lepetit et al., 2021).

2.7 Integration of ESG in Systematic Investment Style

As ESG concerns evolved, integrating ESG in portfolio construction become an important challenge for asset managers and several approaches have been proposed by academics. Regarding the integration of ESG in a factor investing approach, more precisely, on the quality factor, the subject of our study, the literature is far from conclusive.

Some academics support the idea that ESG can be used as a factor, hence, including it in factor models and portfolio construction (Jordan Dekhayser, 2018). Melas, Nagy and Kulkarni suggested that numerical ESG scores can be easily transformed into exposures, forming the basis for a factor model (Melas, Nagy, and Kulkarni 2016). Additionally, Henriksson et al. provide an integration strategy based on two steps: classify the firms using the industry material ESG factors and construct an ESG Good Minus Bad (GMB) factor (Henriksson et al. 2019). Subsequently, this factor could be used to find those firms whose returns depend significantly on the factor, to solve one of the biggest challenges of ESG – the scarcity of data (the strategy is particularly suitable for quantitative investment approach).

While other researchers do recognize ESG as a valid factor. Breedt et al. (2018) studied the consideration of ESG as a factor – a source of alpha above what is already captured by other well know factors – in an equity market-neutral portfolio. They conclude that any benefits are already embedded in the well-defined factors. They report that ESG information yields no additional return, but it does not sacrifice it either. Suggesting that ESG can be incorporated as an investment guide but not a source of alpha. In the research by Ari and West (2020), ESG fails the tests proposed by Beck et al. (2016) to define a factor. The three critical criteria to prove the robustness of a factor are:

1. A factor should be grounded in a long and deep academic literature.
2. A factor should be robust across definitions.
3. A factor should be robust across geographies.

The researchers concluded that ESG is not grounded on long and deep academic literature. Equally, performance results are not robust across regions, nor across definitions.

Even if we cannot prove the robustness of ESG as a risk premium factor, its importance is undeniable. Investors are increasingly looking to align portfolios with their firm's values, seeking to have a positive societal impact and fight climate change. Hence, prioritizing ESG integration in their portfolios. There is also regulatory pressure to increase transparency and standardization in ESG strategies. Concluding, ESG does not need to be a factor for investors to achieve their ESG and performance goals.

2.7.1 ESG and quality investing

The literature shows that companies with high-quality characteristics tend to have higher ESG ratings compared with their peers. Melas, Nagy, and Kulkarni (2016) examine ESG performance in the context of a factor model and concluded that companies with high-quality characteristics tend to have above-average ESG ratings. Subsequently, they performed historical simulations of a systematic quality strategy with gradually improving ESG scores, the results show that improving the ESG profile of a quality strategy has no effect on the information ratio and has only modest impacts on the quality exposure (Melas, Nagy, and Kulkarni, 2017). Zoltán Nagy, Doug Cogan, and Dan Sinnreich (2013) find that ESG tilted strategies outperform the benchmark – MSCI World Index between 2008 and 2010. This period corresponds to a "flight to quality" in stock selection, investors acting defensively and favoring profitable, safe, and stable companies. This is in line with previous findings, suggesting that high-quality companies tend to have good ESG ratings (Nagy et al. 2013).

To understand how an ESG tilt could impact the performance of a quality investment strategy, it might be useful to study the correlation between quality factors and ESG scores. A Russell investment study found that ESG scores are positively but not strongly correlated with quality and value factors. When repeating the analysis using material ESG score, the correlation with quality increases, while no distinguishable change can be observed with value factors (Steinbarth and Bennett, 2018). From these results, we can conclude that adding an ESG tilt to a quality strategy does not compromise the ability to find quality companies.

Bruno, G., Esakia, M., and Goltz, F. (2021) found that ESG strategies (they studied ESG strategies based on U.S. and other developed markets) heavily depend on quality factors. The strategies have significant positive exposure to the high profitability and the low investment factor. This indicates that ESG strategies behave like quality strategies, investing in profitable companies that invest conservatively (Bruno, G., Esakia, M., and Goltz, F. 2021). The same phenomena can be observed with strategies that use a single component of ESG (*e.g.*, focusing on environment, social and governance). The only exception is the ESG momentum strategy – favoring stocks with increasing ESG scores – which does not correlate with the quality strategy. Jordan Dekhayser (2018) by building groups of companies, based on the MSCI World Index, according to the ESG rating, concluded that ESG is related to high profitability, large size, high valuation, high beta, and low residual volatility.

2.7.2 Importance of materiality in ESG assessment

ESG issues are not equally relevant for all companies. Therefore, a materiality assessment is pivotal. The assessment allows scrutinizing only the most critical ESG categories of each company. Incorporating materiality in ESG assessment enables investors and companies to distinguish between companies that score high on ESG issues that are financially material, from those that score high because of metrics irrelevant for their business. Research suggests material ESG scores are better predictors of investment return compared with general ESG scores that are not considered material (Steinbarth and Bennett, n.d.). Researchers found evidence that investors focusing on material ESG categories increase their chance of outperformance (Khan, Serafeim, and Yoon 2016). Materiality is the key to outperformance, as the authors conclude that consideration of non-material ESG factors does not yield better returns and may even lead to underperformance.

3. Company Overview

BPI Gestão de Ativos was founded in 1990, in Portugal, and focuses on the commercial banking business, offering a wide range of financial services to individual, institutional, and corporate customers. BPI GA is Portugal's second-largest asset manager with €7,226 million AuM as of 2020 (BPI Gestão de Ativos, 2020). In 2018, BPI GA was entirely acquired by CaixaBank Asset Management, a leading Spanish financial group with a socially responsible and universal banking model, based on quality and trust.

Sustainable and responsible investing form part of BPI Gestão de Ativos identity. The firm was the first Portuguese signatory of the United Nations Principles for Responsible Investing (UNPRI), a United Nations-supported international network of investors that aim at implementing UNPRI 6 principles, based on environmental, social, and governmental issues. The company is also part of the UN Global Compact and Climate Action 100+, a group of investors aiming to implement the goals of the Paris Agreement. These ambitions are complimented by CaixaBank's comprehensive fundamental investment policies, which aim to integrate ESG considerations across the whole investment universe. Thus, the decision-making process and the array of investments carried out by BPI GA must thoroughly integrate ESG and corporate social responsibility considerations.

BPI's investment products vary from retirement plans, fixed-income funds, life insurance products, funds of funds, equity funds to real estate funds. Equally, its geographic exposure ranges from regional to global, *i.e.*, operating in America, Europe and Asia-Pacific. The bank has managed to put forward a set of investment vehicles that can suit any degree of risk aversion, as well as discretionary investment management products that can be adjusted to the client's risk profile.

4. Data and Methodology

4.1 Data

The input data used in the work project is divided into three main groups: (1) BPI Opportunities fund, a quality-focused portfolio built by BPI GA and our main object of study; (2) investment style factors, used in the regression analyses; and (3) benchmarks, used for performance comparison purposes and robustness checks. The benchmarks selected are MSCI style investing indices based on strategies that are tilted to a specific factor such as quality, value, momentum, or volatility (MSCI World, MSCI World Quality, MSCI World Value, MSCI World Momentum, MSCI World Minimum Volatility). Regarding the investment style factors, three different data providers were chosen – Applied Quantitative Research (AQR), Fama-French, and Bloomberg.

In this section, a description of the BPI Opportunities fund and the factors selected is provided.

4.1.1 BPI Opportunities

BPI Opportunities is a fund built on the MSCI World index, that invests in global stocks, targeting large-capitalization companies in developed markets. By seeking profitable, stable, and low leverage companies, BPI Opportunities aims at creating a global and diversified portfolio of quality companies with low cost and low turnover. Following a semi-automated investment strategy, the fund is constructed using a combination of screening and scoring criteria, and an investment committee assessment to choose the 50 highest quality companies from the MSCI world stock universe that respect the ex-ante risk, liquidity, and sector allocation requirements. Screening constitutes the first step in the investment process of the €141.7 million fund: companies with a market capitalization below $15 billion, high leverage, declining cash flows, poor ESG scores, deteriorating returns on capital and margins are excluded from the investment universe. Subsequently, the scoring of the remaining companies is initiated, relying on a ranking formula and financial indicators such as return on capital, operating margin and their stability to find the 80 highest quality companies. Finally, 50 of these 80 companies are handpicked after assessing their liquidity risks and controlling for risk factors, namely, a tracking error of 3% to 6% of the MSCI World, a GICS sector allocation limit of 20% of active weight, and equally weighted holdings. Holdings are generally quarterly reviewed, however, holdings with weights below 1% or above 3% trigger a reassessment and rebalancing of the portfolio. The same strategy is employed in two other BPI funds which have a regional focus: BPI America and BPI Africa.

4.1.2 Description of Factors

Factor models are considered a reference tool that helps understand and manage the systematic sources of portfolio risk and reward. They provide a detailed composition of portfolio returns into factor exposures and have been widely used by academia and practitioners either to build an investment strategy or as a tool to evaluate risk sources. Throughout our research, we used style factor models seeking to study the underlying risk exposures of BPI's quality-based funds. The ultimate goal is to analyse if BPI's quality strategy has significant exposures to quality as defined by academics and practitioners and if it is delivering alpha and not just risk premium derived from another factor. The Fama-French, Bloomberg, and AQR factors were used to perform the regression analysis.

All the models are based on arbitrage pricing theory; the difference lies in the style factors and the metrics used to define them. Testing with multiple factor models provides a more holistic view of the fund performance, as there is no consensus on the correct definitions of style factors. Moreover, it allows for the comparison and evaluation of the different factor models.

For the sake of simplicity, the three models used in our analysis are hereafter referred to as the Fama-French Factor Model, the AQR Factor Model and the Bloomberg Factor Model.

4.1.2.1 Fama-French factors

Fama and French firstly developed the 3-factor model, an extension of CAPM that aims at capturing two relations: difference in average return grouped by size and difference in average return grouped by price ratios (book-to-market). Then, as the model failed to explain all the excess returns, it was expanded to include profitability (RMW) and investment (CMA) factors. The goal of this extension was to capture the high average returns associated with low market beta and low stock return volatility.

The size and value factors are built using six value weight portfolios formed on size (two size groups) and book-to-market value (three book/market groups). The other factors – RMW and CMA – are built using six value-weighted portfolios and sorted on the characteristic that the factor is capturing. The median of the investment universe is used to split the stock into two groups – small and big – and book/market breakpoints are the 30th and 70th percentiles of the book to market ratio of the investment universe.

- Small Minus Big (SMB) factor: Aims to capture the risk factor related to size, based on the idea that small capitalization companies historically outperformed big capitalization companies. The size factor is built as the spread in the returns of small and big stock portfolios controlling for book-to-market equity.

- High Minus Low (HML) factor: Aims to capture the premium associated with value based on the rationale that high value companies outperform low value (growth) companies and the overall market. It is constructed as the difference in returns between high and low book-to-market ratio companies, controlling for the same weighted average size.
- Market Risk Premium (MRP) factor: It corresponds to the excess market returns over the risk-free (1-month US Treasury Bill).
- Robust Minus Weak (RMW) factor: Captures the difference between the returns on diversified portfolios of stocks with robust and weak operating profitability. As profitability is many times used to describe quality companies, we use this factor as a proxy for the quality factor.
- Conservative Minus Aggressive (CMA) factor: Captures the difference in the returns on diversified portfolios of companies with conservative investment policy (low levels of investment) and companies with an aggressive investment policy (high levels of investment).

As BPI Opportunities is a global fund focused mostly on developed markets, we use Fama and French developed markets factors. Daily factor returns, including dividends and capital gains, in USD, were retrieved from Kenneth R. French data library.

4.1.2.2 AQR factors

AQR differs from the Fama and French model by providing a Quality-minus-Junk factor (QMJ). As the name suggests, it aims at capturing the premium associated with high-quality companies. AQR's quality score is the average of four aspects of quality: profitability, growth, safety, and payout. Following the methodology of Fama and French (1993) and Asness, Frazzini, and Pedersen, (2013), the factor is built as the intersection of six portfolios formed on size and quality. QMJ factor goes long on the top 30% quality companies and short on the bottom 30% junk companies, divided into small and large size companies. Subsequently, final returns are computed as the average of two high-quality minus two low-quality portfolios.

Daily returns on global factors were retrieved from AQR website. All the portfolios are constructed using Fama and French (1993) and Asness, Frazzini, and Pedersen (2013) methodology and they replicate the same stock universe. MKT-RF is the market returns over the 1-month US Treasury Bill. The SMB and HML factors are constructed following Fama and French (1993) and Asness, Frazzini, and Pedersen (2013) definition. The difference lies in how book equity is scaled: Fama and French divide it by the total market value of equity at the end of the year, while Asness, Frazzini, and Pedersen (2013) use the current total market value of equity at the end of each month. We use the factors that follow Fama and French (1993) definition. There is one additional factor, momentum – UMD (Up Minus Down) that aims to capture the premium of well-performing stocks over badly performing stocks. The factor is built as a weighted average of the two high return stocks minus the two low return portfolios considering the returns of the past 12 months, excluding the most recent month.

4.1.2.3 Bloomberg factors

The factor analysis relies on global, size value, momentum, and profitability Bloomberg factors.[1] Profitability, a proxy for quality in our analysis, is a factor that is built on four metrics: return on equity (book measure), return on capital employed, return on assets and EBITDA margin. The market risk premium is not provided and thus computed following Fama and French (1993) approach, that is, the difference between the MSCI World Index returns (proxy for the market return) and the 1-month US Treasury Bill.

[1] Bloomberg size factor, contrary to the other data providers, is built as a portfolio that is long big caps and short small caps (Big Minus Small).

4.2 Methodology

4.2.1 Data handling

The raw data was curated in preparation for empirical work. To avoid biased findings resulting from a short time series, the analysis was run on two different periods: the true portfolio sample period that corresponds to the real portfolio data, *i.e.*, observations since the fund's inception date (30/11/2018 to 10/09/2021), and a joint sample period that includes the real portfolio data plus a backtest of the strategy (01/10/2003 to 10/09/2021). Nevertheless, it should be noted that the provided backtest does not perfectly match BPI Opportunities' current strategy, which may have implications for our analysis.

The historical prices (denominated in euros) of BPI Opportunities were retrieved from Bloomberg for both periods. Moreover, the historical prices of the MSCI World (BPI Opportunities Benchmark), as well as the Bloomberg factor, were retrieved from the aforementioned data providers.

The data and factors are resampled to weekly frequency, as Bloomberg factors are only available in weekly frequency. The resampling from daily to weekly frequency data, for the remaining data providers, was done by transforming arithmetic returns into logarithmic returns and summing them for each week, starting on Wednesday (to match the Bloomberg dataset) – taking advantage of the time additivity of logarithmic returns. Logarithmic returns are assumed to follow log-normal distributions. Hence, this conversion ensures that the factor returns follow a normal distribution, a pivotal assumption for inference.

The dataset for each data provider contains 140 observations for the *true sample period* and 932 observations for the *joint sample period*.

In order to test for the presence of heteroskedasticity, we used the Breusch-Pagan Test. Whenever the Lagrange multiplier p-value is below 5%, residuals are heteroskedastic for the 95% confidence interval. Whereas if it is above 5%, the residuals are homoscedastic, for the same confidence interval. For the cases in which heteroskedasticity is present, we chose to integrate Newey-West standard errors, to improve the robustness of the model as well as the precision of our estimates. Another advantage of this type of robust standard errors is that they are also robust to autocorrelation.

4.2.2 Currency adjustments

In the scope of this study, we are looking at portfolio returns from a euro investor's perspective; thus, the factors need to be converted into the respective currency – in this case, euros – to avoid skewed estimations for alphas and betas and to draw reliable conclusions.

As pointed before, factor returns were retrieved from open databases such as AQR, Kenneth French's data library and Bloomberg. Except for the latter, these factors are provided in US dollars even for non-US and global stock markets.

Following the methodology suggested by Glück, Hübel, and Scholz (2020), we converted the factor returns expressed in US dollars to euros, achieving unbiased coefficient estimates in the regressions (Glück, Hübel, and Scholz 2020). For long-short factors (such as SMB, HML and MOM) and for MRP, the conversion is given by:

$$(5) \quad r_{eur} = \left(\frac{1}{1+R_{usd/eur}}\right) \times r_{usd}$$

Where r_{eur} is the return of a factor converted to euros, $R_{usd/eur}$ is the USD/EUR exchange rate return and r_{usd} is the factor return originally in dollars.

The relevant USD/EUR exchange rate return is obtained as the percentage change of the USD/EUR time series retrieved from Bloomberg (from January 2000 to September 2021).

In the case of Bloomberg, the global factors are first built for each country, being expressed in local currency, and then converted to global through a weighted average of the country-specific factors. The returns are thus expressed as a weighted average of different exchange rates returns, being that there is no precise and accurate way of performing the return decomposition and converting it to euros, without leading to biased results, due to the lack of an exchange rate that considers all the different currencies embedded in the factors. Still, given the major representativeness of USD, and in the absence of an appropriate rate, we have resorted to the USD/EUR exchange rate. We also present the results in dollars (*Annex 36 & Annex 37*), to be able to draw conclusions without such heavy currency distortions – always keeping in mind that when switching the numeraire from a currency to another, that change will only affect the portion of return and risk captured by the return of the specific exchange rate employed.

5. Robustness Check

Before using the factor models on BPI's funds, it is relevant to check how they perform in explaining the style characteristics of the global market. Hence, the robustness check is of paramount importance to analyse whether portfolio factor exposures are corroborated by the selected risk factors and if these are suitable to explain market characteristics.

We regressed each MSCI global style index excess returns – World, Value, Quality, Momentum and Minimum Volatility, minus the risk-free rate – on the different factor models: Fama-French factors, AQR factors and Bloomberg factors, using the OLS regression method. The sample period considered was 2000/01/05 to 2021/08/04 – being that a period of 21 years is satisfactory to check if the factors are properly explaining market-style characteristics. We run the same tests, in euros and in dollars, to check how the currency adjustments affect the explanatory power of the models and the factors exposures.

We expect that the OLS regressions exhibit a non-significant and close to zero alpha and a high explanatory power measured by the R-squared in all models. Moreover, we expect significant coefficients for the factors that represent the investment style of the index. The equations of the 5-Factor Model regressions for each data provider are just as follows:

(6) *FF 5-Factor:* $R_{index,t} - r_{f,t} = \alpha + \beta_1\ (MKT - r_{f,t}) + \beta_2\ (SMB) + \beta_3\ (CMA) + \beta_4\ (RMW) + \beta_5\ (HML)$

(7) *AQR 5-Factor:* $R_{index,t} - r_{f,t} = \alpha + \beta_1\ (MKT - r_{f,t})\ ) + \beta_2\ (MOM) + \beta_3\ (SMB) + \beta_4\ (HML) + \beta_5\ (QMJ)$

(8) *BL 5-Factor* : $R_{index,t} - r_{f,t} = \alpha + \beta_1\ (MKT - r_{f,t}) + \beta_2\ (Momentum) + \beta_3\ (Size) + \beta_4\ (Value) + \beta_5\ (Profit)$

Where index can be the MSCI World Index, MSCI World Quality Index, MSCI World Value Index, MSCI World Momentum Index or the MSCI World Minimum Volatility Index, in dollars or in euros, $r_{f,t}$ *is the 1-month US Treasury return, and the remaining variables are systematic risk factors' returns of each data provider at week t.*

After running the regressions, our results were just like expected. Starting with Fama-French factors, in dollars, the regressions of the MSCI World Index and the MSCI World Quality Index exhibit a statistically significant alpha. Yet, the alpha is close to zero, not representing a threat to the explanatory power of the model. All the other regressions exhibit a not statistically significant alpha. This is a good indicator that the factors can explain the performance of the indices. The adjusted R-squared is high: it varies between 0.87 for the MSCI World Momentum Index and 0.99 for the MSCI World Index when considering the regressions in dollars (*Annex 2)*. The results are in euros are similar indicating that no deterioration of the explanatory power comes with the currency adjustment (*Annex 5*).

The model using AQR factors in dollars provides really good results with the R-squared being not less than 0.87 and none of the world style indices has a statistically significant and high alpha (*Annex 3*). Only the regressions of the MSCI World Index and MSCI World Value Index exhibit a statistically significant alpha and the coefficients are close to 0. Once we convert the variables to euros, we do not observe any major change in the results (*Annex 6*).

For Bloomberg factors, the results in dollars show high explanatory power for all the analysed indices. All the regressions present high adjusted R-squared (varying between 0.88 and 1) and the alphas are either statistically insignificant or significant but close to zero (*Annex*

4). However, the explanatory power deteriorates substantially with the currency adjustment (adjusted R-squared ranges from 0.51 to 0.9) (*Annex 7*). The quality factor (Profit) is not even statistically significant for the MSCI World Quality Index. This effect may result from the fact that Bloomberg global factors are not provided in dollars.[2] Therefore, applying the currency adjustment as if the factors were provided in dollars might generate misleading results.

We perform additional robustness tests for Bloomberg factors, as it is the model with lower explanatory power. Namely, as a considerable share of the indices is invested in the U.S. market, we run centric tests using Bloomberg U.S. factors to check how they perform in explaining both U.S. quality ETFs and the aforementioned MSCI global indices. Nevertheless, we decided not to consider the model based on U.S. factors because, although it is useful and relevant to explain the behavior of U.S. ETFs' returns, it has lower explanatory power than the global factors when explaining the returns of MSCI global indices.

Concluding, the three models are suitable to explain the world market characteristics. Notwithstanding, Fama-French and AQR factors, in euros, have a higher explanatory power, measured by the adjusted R-squared. The model using Bloomberg factors is the one that suffers the largest decrease in explanatory power when converted to euros. Nonetheless, BPI GA may consider extending its factor analysis with factors from other data providers to ensure reliable regressions results that are independent of currency effects.

6. BPI Opportunities Fund – Sector and Geographical Analysis

To better understand the performance of BPI opportunities, this paper compares the fund with the benchmark (MSCI World Index) and an index that captures quality style attributes (MSCI World Quality).

[2] Further explanation is provided in section 4.2.2. Currency adjustments.

6.1 BPI Opportunities versus MSCI World Index

Structural comparison between BPI Opportunities Fund and the benchmark (MSCI World) can provide explanations for the differences in performance (*Annex 8)*. Starting with the geographical allocation, the differences are minor. BPI Opportunities exhibits a lower exposure to the Asia Pacific region (7.2% versus 9.7%), higher exposure to Western Europe (21.8% versus 20.1%), and the exposure to North America is largely identical (69.9% versus 69.7%) (*Annex 9* & *Annex 10*).

However, large differences become visible in the sector allocation (*Annex 11*, *Annex 12* & *Annex 13*) which can be an explanation for the outperformance of BPI Opportunities, when compared to the MSCI World index. BPI Opportunities Fund presents an overweight in the Information Technology (IT) sector compared to the benchmark (+8.2%). Over the same period (*03.12.2018 to 15.09.2021*), the IT sector (considering the performance of the MSCI World Information Technology Index) was by far the best performing (35.6%). This over-exposure to the IT sector and the related performance even offsets the underweight in the second-best performing sector, Communication Services with a performance of +23.7% and relative underweight of -3.7% with respect to the benchmark. In addition, weaker performing sectors such as Financials (+10.6%) were underweighted by a difference of -8.7% relative to the benchmark. Another driver of the outperformance is the little to no exposure to sectors such as Real Estate, Energy, and Utilities. These sectors generated the weakest performance over the sample period. These can be observed in *Annex 14*.

The process of selecting the companies for BPI opportunities is not fully systematic, it also includes a stock-picking component. Therefore, one should also examine how is the Allocation & Selection Effect – for this, we used Bloomberg PORT. The allocation effect describes the underperformance (overperformance) achieved by the portfolio manager by underweighting (overweighting) a specific sector in the portfolio compared to the benchmark.

The selection effect describes the ability of the portfolio manager to achieve over or underperformance by investing in individual stocks (or overweighting them compared to the benchmark).

Due to the active selection of stock picks, an alpha of 27.62% was achieved compared to the iShares Core MSCI World UCITS ETF (based on MSCI World Net Total Return USD Index). This results from a plus of 9.78% from the allocation effect, 18.93% selection effect, and a currency effect of -1.09% (*Annex 17*).

6.2 BPI Opportunities versus MSCI Quality Index

Recalling the sector bias of the quality factor[3], it is expected that BPI Opportunities Fund, which follows a quality strategy, has a similar historical sector exposure (*Annex 15 & Annex 16*). If we now continue the research of Ung et al. (2014) regarding the sector exposure to the period from December 2018 to September 2021, using the MSCI World Quality Index, we can observe that the growth in terms of sector proportions is very similar to BPI Opportunities. This is particularly the case in the Information Technology sector, which shows a significant growth in both the BPI Opportunities Fund and the MSCI World Quality Index. Thus, the sector allocation behaves in line with the academic findings of Ung et al. (2014).

In order to analyse which advantages or disadvantages the actively managed quality fund from BPI has compared to a passive quality ETF, it is worth taking a closer look at the allocation, selection, and currency effects. For this, we chose the iShares Edge MSCI World Quality Factor UCITS ETF (*Annex 18*). The results show that the outperformance of BPI opportunities over the quality ETF is lower, over the observed period, compared to the outperformance over the iShares Core MSCI World UCITS ETF (21.76% compared to 27.62%). This may be explained by the lower allocation effect (-4.78%) and lower currency

[3] For more information refer to Literature Review section 2.4.2 Sector bias of the quality factor.

effect (-0.66%). The selection effect has decreased only marginally (17.64% instead of 18.93%). So, it can be said that the main reason for the outperformance versus the two funds analysed is due to the active selection and the selection effect. This is most easily illustrated by the example of the Health Care sector. Compared to both benchmarks, the sector had a negative allocation effect (~ -1%) but an enormously high positive selection effect (~ +9%). This contributes an average of +8% to the outperformance of the BPI Opportunities Fund, although the health care sector generally underperforms other sectors over the period considered (sector indices comparison above).

Summing up, the overweight of BPI Opportunities in the Information Technology sector (best performing sector over the analysed period), relative to the benchmark – MSCI World, plus, the underexposure to weak performing sectors as financials can explain the outperformance. Moreover, the geographic allocation of BPI Opportunities indicates that global factors will likely be most suitable for the funds' factor analysis.

7. BPI Opportunities – Quality Exposure

The following section presents BPI Opportunities exposure to systematic sources of risk, intending to analyse the main drivers of the fund's performance and verify whether the fund exhibits positive and significant exposure to the respective quality factors.

To further explain our results, we ran rolling regressions for both periods – with a 12-month window for the *true sample period* and a 60-month window for the *joint period* – to assess the stability of BPI Opportunities factor exposures across time (*Annex 19 to Annex 24*).

7.1 Fama-French factor model analysis

The analyses that rely on Fama-French factors, for both time periods under study, have, as a dependent variable, BPI excess returns and as explanatory variables, the market-risk premium, SMB, CMA, RMW, and HML, formed on developed markets as follows:

(9) CAPM: $R_{BPI,t} - r_{f,t} = \alpha + \beta_1 \; (MKT - r_{f,t})$

(10) 5-Factor: $R_{BPI,t} - r_{f,t} = \alpha + \beta_1 \; (MKT - r_{f,t}) + \beta_2 \; (SMB) + \beta_3 \; (CMA) + \beta_4 \; (RMW) + \beta_5 \; (HML)$

Where $R_{BPI,t}$ *is the gross return of BPI Opportunities,* $r_{f,t}$ *is the 1-month US Treasury return, and* $MKT - r_{f,t}$*, SMB, CMA, RMW, and HML are Fama-French systematic risk factors' returns at week t.*

7.1.1 True sample period (30/11/2018 – 10/09/2021)

Exhibit 1: Fama-French factors – True Sample Period

	Fama-French Factors (True Sample period)	
	CAPM	5-Factor Model
const	0.001*	0.000
	(0.001)	(0.000)
MKT-RF	0.869***	0.951***
	(0.024)	(0.020)
SMB		-0.328***
		(0.053)
CMA		-0.044
		(0.099)
RMW		0.217***
		(0.082)
HML		-0.198***
		(0.050)
Observations	140	140
R^2	0.902	0.961
Adjusted R^2	0.901	0.959
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01

Exhibit 1 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the Fama French 5-Factor Model, over the true sample period (EUR).

By using Fama-French developed market factors, in the true sample period, BPI Opportunities displays a slightly positive alpha of 0.001 under the CAPM model, which is absorbed when we include other systematic risks. As for the 5-Factor model, CMA and RMW are the pivotal factors that serve as a proxy for quality – RMW, which captures the premium associated with the more profitable companies, has a statistically significant coefficient of 0.217, at the 1% significance level. However, the exposure to the investment factor (CMA) is not significant. Additionally, MKT-RF presents a high and significant coefficient of 0.951 and SMB presents a negative coefficient which goes in line with our expectations since BPI has a low tracking error relative to the benchmark and invests in large-capitalization companies. The R-squared increases from the simple CAPM model to the 5-Factor, showing that factors other than the market are important in explaining BPI Opportunities performance.

7.1.2 Joint sample period (01/10/2003 – 10/09/2021)

Exhibit 2: Fama-French factors – Joint Sample Period

	Fama-French Factors (Joint Sample Period)	
	CAPM	5-Factor Model
const	0.001***	0.001***
	(0.000)	(0.000)
MKT-RF	0.835***	0.936***
	(0.011)	(0.011)
SMB		-0.236***
		(0.027)
CMA		0.336***
		(0.041)
RMW		0.142***
		(0.040)
HML		-0.469***
		(0.026)
Observations	932	932
R^2	0.865	0.915
Adjusted R^2	0.865	0.915
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01

Exhibit 2 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the Fama-French 5-Factor Model, over the joint sample period (EUR).

In the joint sample period, the explanatory power increased both for the CAPM and the 5-factor model. Additionally, all the factors present statistically significant estimates. The coefficients go in line with our expectations: BPI invests only in big capitalization companies; therefore, it is reasonable to have a negative coefficient of -0.236, at the 1% significance level, to the SMB factor. This factor captures the premium associated with small-sized firms compared to large-capitalization companies. The coefficient on the value factor (HML) is also negative, in line with the literature that indicates that value and quality are negatively correlated. The quality factors: RMW and CMA present positive and statistically significant, at a 1% significance level. The effect is larger for the investment factor that presents a coefficient of 0.336, while the exposure to the profitability factor is slightly lower: β = 0.142. The results indicate the BPI opportunities are capturing the premium associated with profitability companies and conservative investment policies.

7.2 AQR factor model analysis

The analyses that rely on AQR factors, for both time periods under study, have, as a dependent variable, BPI excess returns, in euros, and, as explanatory variables, the market-risk premium, MOM, SMB, HML and QMJ factors, in euros, just as follows:

(11) CAPM: $R_{BPI,t} - r_{f,t} = \alpha + \beta_1 \ (MKT - r_{f,t})$

(12) 5-Factor: $R_{BPI,t} - r_{f,t} = \alpha + \beta_1 \ (MKT - r_{f,t}) + \beta_2 \ (MOM) + \beta_3 \ (SMB) + \beta_4 \ (HML) + \beta_5 (QMJ)$

Where $R_{BPI,t}$ *is the gross return of BPI Opportunities,* $r_{f,t}$ *is the 1-month US Treasury return, and* $MKT - r_{f,t}$*, MOM, SMB, HML, and QMJ are AQR systematic risk factors' returns at week t.*

7.2.1 True sample period (30/11/2018 – 10/09/2021)

Exhibit 3: AQR factors – True Sample Period

	AQR Factors (True Sample period)	
	CAPM	5-Factor Model
const	0.001*	0.001
	(0.001)	(0.001)
MKT-RF	0.865***	1.007***
	(0.026)	(0.028)
MOM		-0.053
		(0.036)
SMB		-0.098
		(0.078)
HML		-0.351***
		(0.059)
QMJ		0.310***
		(0.082)
Observations	140	140
R^2	0.886	0.934
Adjusted R^2	0.886	0.931
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01

Exhibit 3 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the AQR 5-Factor Model, over the true sample period (EUR).

As for the true sample period, the explanatory power of these factors increases by 5 pp when transiting from CAPM to the 5-Factor Model, being that alpha is absorbed by the new explanatory variables and becomes insignificant. Since the main goal is to assess whether BPI's strategy is associated with quality investing, this model suggests that it has statistically significant and positive exposure (0.31) to Quality-minus-Junk. Conversely, given that quality and value are negatively correlated, BPI has a negative exposure to HML of -0.351 and insignificant exposure to SMB. Due to the fund's target tracking error, bounded to [3%, 6%], it is reasonable to have a high and significant beta coefficient on the market, around 1, and negative exposure to momentum. For the significant coefficients, all of them are significant at the 99% level confidence interval.

7.2.2 Joint sample period (01/10/2003 – 10/09/2021)

Exhibit 4: AQR factors – Joint Sample Period

	AQR Factors (Joint Sample Period)	
	CAPM	5-Factor Model
const	0.001***	0.001**
	(0.000)	(0.000)
MKT-RF	0.813***	0.985***
	(0.012)	(0.024)
MOM		0.014
		(0.019)
SMB		-0.030
		(0.046)
HML		-0.275***
		(0.039)
QMJ		0.412***
		(0.053)
Observations	932	932
R^2	0.831	0.873
Adjusted R^2	0.830	0.873

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Exhibit 4 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the AQR 5-Factor Model, over the joint sample period (EUR).

In the joint sample period, the explanatory power of the model decreased but not significantly. We can observe a slightly positive, but practically null, significant alpha at the 5% significance level, for the 5-Factor Model. When going from the true sample period to the joint sample period, the coefficient on the QMJ factor becomes more positive, benefiting from a 0.102 increase. The MKT and HML factors remained significant at the 1% significance level, suffering only a minor decrease in absolute terms.

7.3 Bloomberg factor model analysis

The following analysis is run using Bloomberg's global factors. BPI excess returns represent the dependent variable, the market-risk premium, Momentum, Size, Value, and Profit constitute the independent variables. The model is given by the following formula:

$$(13)\ \text{CAPM: } R_{BPI,t} - r_{f,t} = \alpha + \beta_1\ (MKT - r_{f,t})$$

$$(14)\ \text{5-Factor: } R_{BPI,t} - r_{f,t} = \alpha + \beta_1\ (MKT - r_{f,t}) + \beta_2\ (Momentum) + \beta_3\ (Size) + \beta_4\ (Value) + \beta_5\ (Profit)$$

Where $R_{BPI,t}$ is the gross return of BPI Opportunities, $r_{f,t}$ is the 1-month US Treasury return, and $MKT - r_{f,t}$, Momentum, Size, Value, and Profit are Bloomberg systematic risk factors' returns at week t.

7.3.1 True sample period (30/11/2018 – 10/09/2021)

Exhibit 5: Bloomberg factors – True Sample Period

	Bloomberg Factors (True Sample period)	
	CAPM	5-Factor Model
const	0.001	0.000
	(0.001)	(0.001)
MKT-RF	0.865***	0.969***
	(0.052)	(0.059)
Momentum		0.393***
		(0.143)
Size		0.527
		(0.419)
Value		-0.364
		(0.301)
Profit		0.910***
		(0.280)
Observations	140	140
R^2	0.838	0.869
Adjusted R^2	0.837	0.864

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Exhibit 5 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the Bloomberg 5-Factor Model, over the true sample period (EUR).

Regressing BPI's excess returns onto Bloomberg's global factors, no significant alpha can be observed in either one of the models. When looking at the 5-Factor model, significant, positive exposure to the quality factor profitability of 0.91, as well as significant and negative exposure to the value factor (-0.364) can be observed, which goes in line with the negative relationship between the quality and value factors.

Additionally, MKT-RF presents a high and significant coefficient in both models, being that the market beta increases when we go from the CAPM to the 5-factor model. This phenomenon might be explained by the omitted variable bias, namely the omission of the quality factor (*Omitted variable bias*), as the market beta and the quality factor are negatively correlated. Equally, the 5-Factor model reveals a positive exposure to the factor momentum, of 0.393. Finally, the high R-squared indicates that the model performs well at explaining BPI Opportunities performance.

7.3.2 Joint sample period (01/10/2003 – 10/09/2021)

Exhibit 6: Bloomberg factors – Joint Sample Period

	BL Factors (Joint Sample Period)	
	CAPM	5-Factor Model
const	0.001***	0.001**
	(0.000)	(0.000)
MKT-RF	0.673***	0.691***
	(0.029)	(0.039)
Momentum		0.447***
		(0.122)
Size		-0.001
		(0.252)
Value		-0.115
		(0.202)
Profit		-0.016
		(0.315)
Observations	932	932
R^2	0.549	0.560
Adjusted R^2	0.548	0.557

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Exhibit 6 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the Bloomberg 5-Factor Model, over the joint sample period (EUR).

Regressing Bloomberg's global factors onto BPI's excess returns yields a significant, yet residual alpha. We expected a high and statistically significant coefficient on the Profit factor, as it is achieved in the *true sample period*. The reason for the low and insignificant exposure might be the fact that the strategy evolved and therefore, the backtest – data from 2003 until 2018 – does not fully represent the current companies' selection process. The rolling regressions show how drastically the exposure to Profit changes when comparing the *true sample period* with the *joint sample period* (*Annex 23* & *Annex 24*). Additionally, MKT-RF presents a high and significant coefficient in both models and displays an increase in the coefficient as more factors are introduced to the model. Equally, the analysis reveals a statistically significant positive exposure of 0.447 to the factor momentum. Finally, a high R-squared indicates that the model performs well at explaining BPI Opportunities excess returns. The explanatory power increase from the simple CAPM model to the 5-Factor shows that factors other than the market are contributing to explaining BPI Opportunities excess returns.

7.4 Comparing the different data providers

The model using Fama-French factors is the one explaining the highest percentage of BPI Opportunities excess returns both in the *true sample period* and in the *joint sample period*. The coefficients of determination of the 5-factor model are 0.96 and 0.92, respectively. It is also the one showing the highest explanatory power for the MSCI World Quality Index, explaining 96% of the index excess returns. Still, in the *true sample period*, the investment factor (CMA) is not significant, contradicting economic intuition.

The model with AQR factors also performs well with an explanatory power of 93% for the *true sample period* – only slightly lower than the Fama-French model. For the *joint sample period*, the model also exhibits a high R-squared equal to 0.87. Besides, it is observable a positive and statistically significant exposure to QMJ in both sample periods, while the coefficient on the value factor (HML) factor is significant and negative. Also, MKT-RF presents a significant and close to 1 coefficient.

Regarding Bloomberg factors, in the *true sample period*, the model performs well with an 86% explanatory power and a statistically significant and high coefficient on the Profitability factor ($\beta = 0.91$). Still, in the *joint sample period*, the coefficient on the Profitability factor from Bloomberg is negative and insignificant, which does not align with our expectations for the quality strategy under analysis – instead, we would expect a high and significant coefficient.

Likewise, if we look at the coefficient on the Profitability factor when the dependent variable is the MSCI Quality Index, the coefficient is also not significant (*Annex 7*).

Finally, across all models, we observe an increasing exposure to MRP once one moves from CAPM to the 5-factor model. This may be explained by the omitted variable bias: a bias in the OLS estimator when the regressor is correlated with an omitted variable (*Omitted variable bias*). By omitting variables that are relevant to explain the cross-sectional variation in returns, as is the case of the quality factor, the coefficient on the market risk premium is underestimated. As quality and market risk premium are negatively correlated and the strategy has a positive exposure to quality factors (*Annex 25*) when excluding these factors from the model, the coefficient on market risk premium ends up being underestimated.

These findings, in fact, prove that BPI Opportunities excess returns are explained by the AQR, Fama-French and Bloomberg quality factors. The fund presents risk exposures similar to the ones found for the MSCI Quality index providing further evidence that BPI Opportunities behaves as a quality strategy.

8. Macroeconomic Analysis

In the previous section, it was verified that one of the main drivers of BPI Opportunities returns is the quality premium. Just like any other market anomaly, quality does not behave equally under different macroeconomic environments. In order to provide useful insights for the client, such that he can anticipate the behavior of this premium, this paper tried to assess how different macroeconomic variables interact with the QMJ factor.

The existing literature indicates that the quality premium outperforms most strongly in market downturns.[4] The following analysis shows how the behavior of major macroeconomic

[4] Further explanation is provided in the previous section: 2.4.1 Quality under different macroeconomic environments.

indicators affects the Quality-minus-Junk risk premium. Due to insufficient global macroeconomic indicators, U.S-based macro indicators have been used. This decision is supported by the fact that BPI Opportunities has a 70% geographic exposure to U.S. companies and that the U.S., as the world's largest economy, has many contagion effects on other economies. Thus, in the absence of sufficient global macro indicators, U.S-based metrics serve as the best proxy for world-based indicators. To produce accurate results and be consistent with the geography of the used macro variables, U.S. QMJ risk premium is used in the following analysis. For our tests, we used the OLS model. The regression equation is given by:

$$(15)\ QMJ = \alpha + \beta_1\ (\Delta CPI) + \beta_2\ (\Delta VIX) + \beta_3\ (\Delta Unemployment\ rate) + \beta_4\ (\Delta Consumer\ Sentiment) + \beta_5\ (\Delta Copper\ Prices) + \beta_6\ (\Delta Oil\ Prices) + u$$

Where the U.S. quality premium – retrieved from AQR database – is the dependent variable, and the explanatory variables are the changes (Δ) in CPI, VIX, unemployment rate, consumer sentiment as well as copper and oil prices – retrieved from FRED database., for the period of 02/1990-08/2021.

Monthly data spanning over the sample period starting February 1990 until August 2021 was used to run the analysis. While there are a lot more macroeconomic variables affecting the behavior of the quality premium, we decided to focus the analysis on the most relevant indicators. Including "everything but the kitchen sink" in the model increases the risk of multicollinearity and the inflation of the estimators' standard errors, affecting the results of our model. For this analysis, we initially considered a universe of 15 macroeconomic variables. However, to control for multicollinearity, we no longer considered macroeconomic variables with correlation coefficients above 0.5 – ending up with six metrics, as mentioned above.

Exhibit 7: Macroeconomic Model

	Macroeconomic Model
const	-0.001
	(0.003)
CPI	0.222**
	(0.097)
VIX	0.044*
	(0.007)
Unemployment Rate	-0.018*
	(0.011)
Consumer Sentiment	-0.044*
	(0.026)
Copper Prices	-0.061*
	(0.022)
Oil Price (WTI)	-0.017
	(0.014)
Observations	378
R^2	0.214
Adjusted R^2	0.202
Standard errors in parentheses	p<0.1; p<0.05; **p<0.01

Exhibit 7 shows the regression output of the American QMJ factor returns on CPI, VIX growth, Unemployment rate growth, Consumer Sentiment, Copper, and Oil Price Growth (from FRED database), in dollars, over the period from February 1990 until August 2021.

According to our model, the macroeconomic indicators *Δ* CPI, *Δ* VIX, *Δ* Unemployment Rate, *Δ* Consumer Sentiment, and *Δ* Copper Prices have a significant impact on the QMJ risk premium at a common confidence interval of 90%. Only the *Δ* Oil price (WTI) does not have a significant p-value. The fact that the oil price is not significant can be attributed to the moderate correlation with the copper price (0.37) (*Annex 26*). Nevertheless, it was included in the model because it is a relevant macroeconomic variable and can be seen as an indicator of economic growth. All the significant variables have coefficients that go in line with what is expected in terms of economic theory:

- *Δ* **CPI:** Using the monthly Year-on-Year percentage change of the Consumer Price Index (CPI), the highest coefficient can be observed (0.2225). This means that if the Year-on-Year percentage CPI change increases by one unit, the QMJ yield is expected to increase by 0.2225 holding all other independent variables constant. The reason for this is that, in times of high inflation, companies that are considered quality – meeting quality criteria elaborated earlier – have stronger balance sheets to better cope with real currency devaluation, have higher margins and are therefore less exposed to cost inflation per unit of sales, and often have more market power (pricing power) to be able to pass on inflation to customers by increasing prices without having to accept large-scale losses to their customer base.

- **Δ VIX**: Using the monthly percentage change in the volatility index (VIX), we measure the sudden surge or downturn in the VIX. Our results show that a one-unit increase in this metric (ceteris paribus) suggests an increase in the QMJ return of 0.0442. The VIX reflects the market's volatility expectations over the following 30 days and a high VIX has a positive effect on the quality risk premium, as the VIX is seen by market participants as a measure of the level of risk, fear, and stress in the market. Therefore, our positive coefficient goes in line with the literature.
- **Δ Unemployment Rate:** In our regression, we have considered a monthly percentage change between the monthly unemployment rates as this is more indicative of the significance of jumps in the labor market trend. Intuitively, one would think that there would be a positive coefficient here, since a strong and significant increase in the unemployment rate is an indicator of a weakening economy and thus of a higher quality premium. However, our coefficient is small and negative (-0.0176) which implies that an increase of the percentage change of the monthly unemployment rate by one unit (ceteris paribus) the QMJ return will decrease by -0.0176. This phenomenon can be explained by the Phillips curve. The Phillips curve states that there is a negative relationship between inflation (CPI) and the unemployment rate (Phillips, 1958). This can also be seen in our correlation matrix (*Annex 26*) and explains why our model produces a marginal but negative coefficient for the unemployment rate.
- **Δ Consumer Sentiment**: Provided by the University of Michigan, the Consumer Sentiment Index (MCSI) is a predictor of future consumer confidence and spending. Therefore, it is an indicator of future economic strength. By analysing the percentage

monthly change in the MCSI, it is easier to observe implications about trend changes in consumer sentiment. A one-unit increase in this metric (ceteris paribus) suggests a -0.0439 decrease in QMJ returns. Based on our knowledge that the quality premium performs best in economic downturns, our coefficient of -0.0439 makes economic sense. Simply put, the better the consumer sentiment, the better the outlook for the economy, and hence the lower the QMJ. Conversely, if consumer confidence decreases, flight to quality is likely to happen due to the bad economic outlook.

- **Δ Copper Prices:** Copper is a fundamental raw material used in many industries and products. In general, rising copper prices indicate strong copper demand and thus a growing global economy. Falling copper prices may indicate sluggish demand and an impending economic slowdown – the perfect environment for the outperformance of QMJ. Therefore, copper prices are reasonably well suited as an indicator of future economic activity. Using our model and the percentage change in copper prices a coefficient of -0.0610 can be determined which implies that a one-unit increase in this metric (ceteris paribus) implies a decrease of QMJ returns of -0.0610.

A visual breakdown of all significant indicators by the magnitude of their coefficients can be found below.

Exhibit 8: Magnitude of coefficients of macroeconomic regression

Exhibit 8 plots the magnitude of the coefficients of the macroeconomic factors used in the macro regression, showing how each macro variable interacts / correlates with the US QMJ factor returns, for the sample period of February 1990 to August 2021.

Let us now relate these results of our macroeconomic analysis to the BPI Opportunities fund. In Section 7.2, we found that the fund has high exposure to the QMJ factor (true sample period: 0.3104; joint sample period: 0.4123). Consequently, there is a close relationship between the macroeconomic factors that affect the returns of the QMJ factor and the returns of the portfolio itself. It can be concluded that on one hand, BPI Opportunities can potentially achieve a certain outperformance in the event of high inflation (CPI) or a sharp increase in the VIX due to the exposure to the QMJ factor. On the other hand, underperformance by the exposure to the QMJ factor could be expected in the event of sharply improving unemployment figures, a sudden rise in consumer sentiment, and a rapid increase in copper prices.

To sum up, BPI GA should pay close attention to a rise in consumer sentiment and copper prices, as well a decrease in the CPI, VIX, and unemployment rate as these are indicators of a positive economic outlook. During these times, the quality premium is meant to underperform, suggesting that the client might want to revisit its strategy.

9. Extending BPI's Quality Investing Strategy

Considering the current quality strategy and the value-added of the aforementioned macroeconomic analysis – which allows BPI GA to redefine its course of action based on evidence – this paper tries to improve the core strategy of BPI Opportunities based on the findings stated in Section 2.

BPI GA provided its current model for BPI Opportunities, as well as comprehensive financial data for the whole investment universe (MSCI World), extracted from FactSet and Bloomberg – which is consistent across the analysed period.

The regression analyses for the different strategies' returns were made using AQR factors since we are particularly interested in evaluating the exposure to the QMJ factor – the factor proven to be the most significant in explaining the quality risk premium (

Annex 3 & *Annex 6*)[5]. The equation used for each strategy's regression is as follows:

$$(16)\ \ R_{strategy,t} - r_{f,t} = \alpha + \beta_1\ (MKT - r_{f,t}) + \beta_2\ (MOM) + \beta_3\ (SMB) + \beta_4\ (HML) + \beta_5\ (QMJ)$$

Where strategy can be (1) the standard quality-only strategy, (2) a quality strategy with value calibration, (3) an ESG-tilt quality strategy with two different weighting schemes (ESG tilt 1 and ESG tilt 2), and (4) a long-short strategy with two allocation schemes (100/100 and 130/30), $r_{f,t}$ is the 1-month U.S. Treasury return, and MKT$-\,r_{f,t}$, MOM, SMB, HML, and QMJ are AQR systematic risk factors' returns at week t.

9.1 Combining quality and value

9.1.1 Description of strategy

Evidence gathered in the Literature Review points to the fact that joining quality and value yields superior risk-adjusted returns. Further research suggests the use of a bottom-up strategy when building a multifactor strategy: combining securities with exposure to different style factors in a single strategy.[6] Thus, a bottom-up strategy that integrates simultaneously companies with quality and value characteristics was pursued, avoiding neutralization of the exposures that might result from the linear combination of a portfolio that follows a value strategy with the quality companies' portfolio.

Hence, instead of ending up with no exposure to either factor, we propose an investing strategy that simply adds a value calibration to a quality portfolio. More precisely, we apply the exclusion filters and rank the companies according to the quality model defined by BPI and pick the 80 top-ranked securities. Then, we exclude the 30 bottom value companies from the previously defined universe, aiming to find quality assets that exhibit value characteristics and thus not paying premium prices.

[5] For more information refer to section 5 Robustness Check.
[6] For more information refer to Literature Review section 2.5.5 Top-down vs bottom-up approach factor investing strategies.

The ability to capture value premium varies across value measures. Therefore, before building the model, we revise different metrics in order to include the ones that prove to be significant through time in explaining the value premium. We arrive at three traditional value metrics: earnings yield, sales to price ratio, and cash flow yield. Earnings yield is the strongest and most significant factor in absolute terms according to FTSE Russell research; sales to price and cash flow yield also prove to be significant over time and show superior cumulative performance when compared to other value metrics (FTSE 2014). Since we did not have access to forward yields, trailing yields (previous 12 months figure over current share price) were used instead, to strengthen our value measurement. Using both trailing and actual metrics, we were able to construct a value ranking scheme and determine the relative value of each security (with higher yields/ratios indicating greater value).

9.1.2 Results

The combination of value and quality results in a reduction of the risk-reward ratio (*Exhibit 13*).[7] The quality and value strategy developed for this thesis attempts to achieve steadier returns through the integration of value indicators in a quality strategy. The objective is to identify high-quality assets without paying a premium. Leveraging on the negative correlation of quality and value, a reduced standard deviation of 14.06% compared to 15.16% of the quality-only strategy was achieved. However, while a slight reduction in standard deviation can be observed, the reduction in average annual returns outweighs these improvements as the annual returns reduce from 19.67% to 16.61%. Thus, the risk-reward ratio decreases from an excellent 1.3 to 1.18. This suggests that the strategy developed picks stocks with higher value characteristics at the expense of its quality characteristics. However, by analysing the strategy's factor exposure, this hypothesis can be rejected. Introducing value considerations to the existing quality strategy

[7] The risk-reward ratio is given by: $\frac{Annual\ Returns}{Standard\ Deviation}$

reduced the negative value coefficient HML from -0.46 to -0.26, while the quality coefficient QMJ increased from 0.17 to 0.28. Additionally, market beta reduced from 0.98 to 0.94. All coefficients are statistically significant on the 99% confidence interval, the adjusted R-squared reduces marginally from 0.772 to 0.769 (*Annex 32*). The decrease in the negative coefficient of the value factor, as well as the increase in the quality coefficient, suggests that the proposed strategy increases the quality exposure, while also reducing the negative impact of the portfolio's value exposure. Thus, the poor performance of the strategy has to be explained differently. One explanation might be the poor performance of value strategies over the past few years, with growth companies experiencing a much better performance. Moreover, the reduction in market beta might be able to explain some reduction in returns as the market tends to drive much of the portfolio's performance.

Exhibit 9: Risk-Return Comparison I (2012-2021)

Visualization of the annualized risk-return profiles of the new strategies (quality-value and quality-only) and BPI Opportunities. The quality-only strategy shows the most attractive risk-reward ratio (1.30), followed by BPI Opportunity (1.23) and the quality-value strategy with the worst risk-reward ratio (1.18).

9.2 Long quality and short junk

9.2.1 Description of strategy

Literature suggests that long-short strategies in quality investing have superior performance compared to long-only strategies as they benefit from the upward potential of quality and downward potential of junk[8]. Following this evidence and considering that BPI Opportunities is a long-only investment strategy, we replicate its quality strategy as a long-short portfolio. To that end, we sort securities based on the regular scoring scheme without performing exclusions to avoid removing junk stocks from the investment universe. Then, we select the top 50 companies to be the long positions and the bottom 50 to be the short positions.

Concerning the asset allocation, we first tested a market neutral strategy with 100% weighting in long positions and -100% in short positions. However, as referred in the Literature Review, market neutrality prevents institutional investors from performing in line with the market. Moreover, short selling puts an investor in a position of unlimited risk and capped reward since the most they can gain is the stock price when shorted while the most they can lose is infinite as, in theory, the stock price can increase forever. Hence, we decided to test an alternative more compliant with BPI GA's risk considerations – the 130/30 strategy in which a manager puts more emphasis on the long position (130) rather than the short position (-30).

The 130-30 strategy refers to an investing methodology commonly used by institutional investors that implies allocating 130% of starting capital to the long position by taking 30% of the starting capital from shorting stocks. Also known as "beta one" strategies, these 130/30 portfolios are targeted to have a net market beta of 1 and generate positive alpha, therefore producing greater returns compared to the market without taking on added systematic risk.

9.2.2 Results

The long-short strategy aims to harvest profits from quality and junk by going long on quality stocks while shorting junk stocks. To assess the performance, two portfolios were tested: one with a negative weight of 100% on the short, and 100% on the long, and another one with 30% on the short, and 130% on the long. The resulting risk-reward ratios differ significantly.

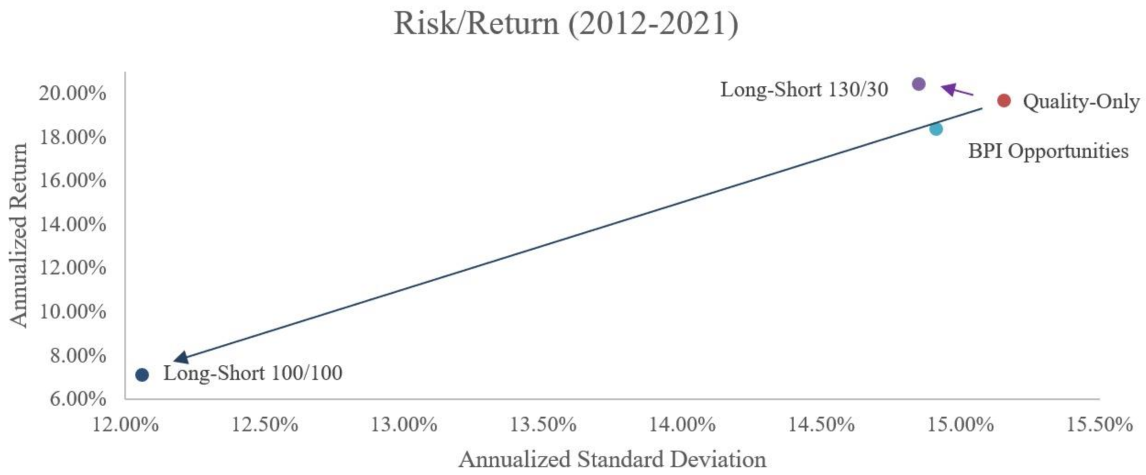
[8] For more information, refer to Literature Review section 2.6 Long-only and long-short strategies in quality investing.

While the 130/30 portfolio exhibits an exceptional risk-reward ratio of 1.37, the 100/100 strategy performs poorly with a risk-reward ratio of 0.59 (*Exhibit 13*). This difference in returns can likely be explained by the relative market neutrality of the 100/100 strategy. The 100/100 exhibits a low market beta of 0.21 as well as momentum, size, value, and most notably quality coefficients of 0.17, 0.27, -0.44 and 0.52, respectively. All coefficients are statistically significant on the 99% confidence interval, the adjusted R-squared is equal to 0.15 and very low (*Annex 32*). The large, positive coefficient on quality is to be expected as the strategy mimics strategy investing in its purest form and indicates that the strategy's performance is highly dependent on the quality factor. Additionally, the low market beta indicates that the strategy is missing out on much of the market return. This might explain the poor performance of the strategy with an average annual return of 7.11%. Nevertheless, it appears to have a positive effect on the standard deviation, with a reduction in standard deviation to 12.1%.

In contrast, the 130/30 strategy does exceptionally well. It generates the highest average annual return of 20.42% of all strategies tested, while also exhibiting a low standard deviation equal to 14.85% (*Exhibit 13*). The strategy does not aim for market neutrality. Hence its market beta, while significantly lower than in other strategies tested, is significantly higher than the 100/100 strategy and amounts to 0.87. Moreover, the strategy exhibits significant momentum, size, value, and quality factor exposure, with coefficients equal to 0.11, 0.12, -0.57 and 0.24 (*Annex 32*). All coefficients are statistically significant on the 99% confidence interval and the adjusted R-squared increases significantly to 0.63. The strategy's high average annual returns are likely related to the leverage that de facto allows for use of 160% of the portfolio's assets. Equally, it benefits from a high market beta, allowing the strategy to capture market return.

The two long-short strategies share certain characteristics. Analysing the factor exposure of the strategies, one can observe the positive size coefficient of both strategies as the exclusion of companies with a market capitalization of below USD 15 billion is not performed (exclusion criterion that is applied in the quality-only strategy). While the results of the 130/30 strategy appear remarkable, one should also point out that they omit relevant cost factors. Neither of the strategies accounts for trading costs nor the need for beta hedging that might hamper returns significantly.

Exhibit 10: Risk-Return Comparison II (2012-2021)



Visualization of the annualized risk-return profiles of the new strategies (Quality-Only, Long-short 130/30, and Long-Short 100/100) and BPI Opportunities. The creation of the Long-Short strategies yields very different risk-return profiles. While the Long-Short 130/30 strategy improves the risk-return profile of quality-only (1.37 vs 1.30), the long-short 100/100 strategy heavily decreases (0.59 vs. 1.30).

9.3 Quality with an ESG tilt

9.3.1 ESG incorporation

Despite the lack of consensus in the literature on whether ESG should be considered a risk premium factor, this paper attempts to incorporate it in the factor models. To further investigate how the quality and ESG factors interact, under the light of past research that suggests a positive correlation. The analysis of the relationship between these two variables was conducted using the Pedersen et al. (2020) ESG Factor. This factor replicates the excess returns of an equally weighted portfolio that goes long on companies with excellent ESG scores and short on those with very poor ones.

Since this chapter focuses on BPI Opportunities' quality strategy with different tilts, as a starting point, we regressed BPI Opportunities excess returns on AQR, Fama-French, and Bloomberg five factors, plus the Pedersen et al. (2020) ESG factor, following the equations below:

$$(17)\ R_{BPI,t} - r_{f,t} = \alpha + \beta_1 (MKT - r_{f,t}) + \beta_2 (MOM) + \beta_3 (SMB) + \beta_4 (HML) + \beta_5 (QMJ) + \beta_6 (ESG)$$

$$(18)\ R_{BPI,t} - r_{f,t} = \alpha + \beta_1 (MKT - r_{f,t}) + \beta_2 (SMB) + \beta_3 (CMA) + \beta_4 (RMW) + \beta_5 (HML) + \beta_6 (ESG)$$

$$(19)\ R_{BPI,t} - r_{f.t} = \alpha + \beta_1 (MKT - r_{f,t}) + \beta_2 (Momentum) + \beta_3 (Size) + \beta_4 (Value) + \beta_5 (Profit) + \beta_6 (ESG)$$

Where equation (17) refers to the AQR Model, equation (18) to the Fama-French Model, and equation (19) to the Bloomberg Model. In all equations, $R_{BPI,t}$ stands for BPI Opportunities return, $r_{f,t}$ is the 1-month U.S. Treasury Bill return and the remaining variables are each data provider's factors returns, for month t.

This inclusion allowed us to verify that the quality factor is positively correlated with the ESG factor in all models, indicating that ESG integration does not affect a portfolio's ability to capture quality factor exposure, which is in line with the literature. When using the AQR Model, QMJ has a correlation coefficient of 0.45 with the ESG factor (*Annex 31*). Similarly, Fama-French's quality factors – RMW and CMA – exhibit a positive correlation of 0.25 and 0.21 with the ESG factor, and Bloomberg's profitability factor exhibits a coefficient of 0.53 (*Annex 31*). When looking at the regressions tables of the three data providers *(Annex 27, Annex 28, Annex 29),* it is notorious that the magnitude of the respective profitability factors is enhanced by the inclusion of the ESG Factor, even though the latter is not statistically significant in none of the models. As a matter of fact, when transiting from the 5-Factor Model to the 6-Factor, AQR's quality factor coefficient increases by 0.029 pp. The same is verified when using Fama-French or Bloomberg factors, with an increase of 0.002 in the RMW factor and an increase of 0.147 pp in the Profitability factor. Thus, these results act as a checkpoint that validates the success of quality and ESG together.

9.3.2 *Description of strategy*

ESG and quality are excellent complements as they capture two different dimensions of sustainability – non-financial and financial (Jordan Dekhayser, 2018). Based on our results and the evidence from the literature, a combination of ESG and quality can be powerful. Thus, we developed a strategy to incorporate ESG in the BPI quality strategy in a more systematic way. At the present, BPI Opportunities applies a combination of exclusion and adjustment of WACC to integrate ESG considerations. Stocks with ESG scores below a given MSCI ESG rating threshold (CCC) are excluded from the initial stock universe. Additionally, the strategy puts a lot of weight on a value creation rank – a simplified discounted cash flow model that adjusts its WACC according to a company's ESG score. The new ESG strategy adds a new dimension to existing exclusion criteria, systematically over or underweighting companies depending on its ESG rating. After applying the quality screening and ranking process, the top 50 quality companies are ranked according to their ESG score. Subsequently, portfolios with varying weights are built. Two different weights have been tested. The first strategy (ESG tilt 1) assigned a weight of 2.5% to the 16th best ESG companies, moderate ESG companies receive a weight of 2%, and the worst 16th received a weight of 1.5%. The second strategy (ESG tilt 2) increased the overweight on the 16 companies with the highest ESG score to 3% and reduced the weight given to the 16 companies with the lowest ESG score to 1%.

All scores used in this strategy are industry adjusted. The goal of the strategy is to systematically tilt the portfolio towards companies with higher ESG scores while keeping the funds' main objective: high-quality exposure.

9.3.3 *Results*

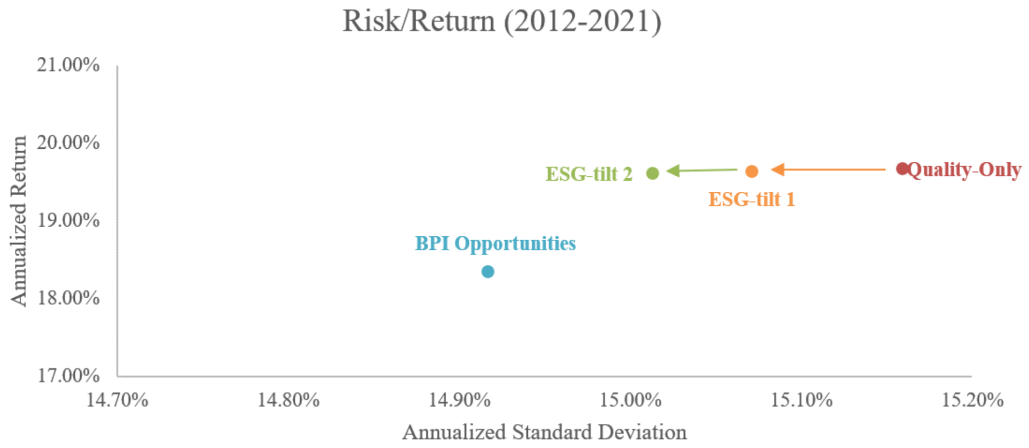
We tested the ESG tilt strategy considering two different tilts: a more conservative one that under/-overweight companies by 0.5% – ESG tilt 1 – and a more drastic one that over/-underweights the companies by 1% – ESG tilt 2. Both strategies resulted in lower annualized standard deviation compared with the strategy that relies solely on the quality metrics (*Exhibit 13*). The overall goal of the strategy, increasing the ESG profile of the portfolio, was reached. By incorporating the ESG tilt 1, the ESG performance increase from a 7.04 score (A) to a 7.39 score (AA) according to MSCI ESG scoring. While as for the ESG tilt 2, the ESG performance increase from a 7.04 score (A) to a 7.74 score (AA).

Moreover, the improved ESG profile was reached without sacrificing the financial performance, the returns are in line with the quality-only strategy, while ESG strategies seem to offer downside risk protection (*Exhibit 13*). These results are in line with academic research, (Giese et al. 2019) showed that companies with high MSCI ESG ratings exhibit lower idiosyncratic and systematic risk. Sustainable funds may even offer stability in periods of uncertainty showing a lower increase in standard deviation (Morgan Stanley Institute for Sustainable Investing, 2019).

Analysing the factor exposures using AQR factors, the two ESG strategies perform similarly: all the coefficients are statistically significant in both strategies and the coefficients on the QMJ factor even slightly increased when compared with the strategy focused solely on quality (*Annex 32*) indicating that the ability to get exposure to quality was not compromised. Moreover, the explanatory power of the model remains high, exhibiting an adjusted R-squared of 78%.

Ultimately, we prove that quality and ESG are a great combination, even capable of extending quality exposure. Our results indicate that it is possible to improve the ESG profile of a quality strategy on a systematic basis, without jeopardizing the ability of the portfolio to get quality exposure and even slightly decreasing the downside risk.

Exhibit 11: Risk-Return Comparison III (2012-2021)



Visualization of the annualized risk-return profiles of the new strategies (Quality-Only, ESG-tilt 1, and ESG-tilt 2) and BPI Opportunities. The new ESG-tilt strategies both have slightly lower volatility while having marginally less return and therefore yielding similar risk-reward ratios (Quality-Only: 1.30; ESG-tilt 1: 1.30; ESG tilt 2: 1.32).

9.4 Comparison of the strategies

The ESG tilt 2 as well as long-short 130/30 quality strategy exhibit the highest risk-reward ratios. BPI Opportunities exhibits the third lowest risk-reward ratio of 1.23, while the ESG tilt 2 and long-short 130/30 quality strategies exhibit risk-reward ratios of 1.31 and 1.37 respectively (*Exhibit 13*). These are significantly higher than BPI Opportunities risk-reward ratio but also higher than the quality-only strategy (backtest that replicates BPI's current model) that is equal to 1.3. Thus, it can be inferred that the BPI Opportunities strategy has significantly improved since its inception. Equally, it can be noted that the strategy can be further improved if the tested strategies are adopted. We recommend the use of the ESG tilt 2 strategy, as it increases the risk-adjusted performance of the portfolio, while also improving the portfolio's ESG rating from A to AA. Furthermore, we consider the long-short 130/30 quality strategy to be an interesting option, provided BPI GA's investment mandate allows for shorting. However, prior to implementing such a strategy, it is necessary to adjust the model for trading costs as they might materially impact the performance of the strategy. Finally, we would like to highlight the potential of the developed quality-value strategy. While not performing as good as some of the other strategies, it might prove to be interesting to revisit the strategy when the success of growth stocks and poor performance of value stocks comes to an end.

Exhibit 12: Risk-Return Comparison IV (2012-2021)

Visualization of the annualized risk-return profiles of the new strategies (Quality-Only, Quality-Value, Long-Short 130/30, and ESG-tilt 2) and BPI Opportunities. All new strategies show a better risk-reward profile than BPI Opportunities, except Quality-Value due to the recent historical underperformance of value stocks in the market.

Exhibit 13: Summary statistics for all created strategies

	BPI Opportunities	Quality-Only	Quality-Value	ESG-tilt 2	ESG-tilt 1	Long-Short 130/30	Long-Short 100/100
Return	18,35%	19,67%	16,61%	19,61%	19,64%	20,42%	7,11%
Standard Deviation	14,92%	15,16%	14,06%	15,01%	15,07%	14,85%	12,06%
Risk reward ratio	1,23	1,30	1,18	1,31	1,30	1,37	0,59
Positive Days	56,10%	55,87%	56,10%	56,49%	56,22%	56,99%	51,79%
Daily Skew	-0,45	-0,42	-0,45	-0,40	-0,41	-0,27	-0,18
Daily Kurtosis	12,95	10,72	11,11	10,97	10,88	7,66	5,22
Daily Max return	8,62%	7,91%	6,79%	7,96%	7,93%	7,42%	4,14%
Q3	0,54%	0,55%	0,52%	0,55%	0,55%	0,57%	0,46%
Med	0,10%	0,10%	0,08%	0,10%	0,10%	0,11%	0,03%
Q1	-0,35%	-0,37%	-0,35%	-0,36%	-0,37%	-0,39%	-0,40%
Daily Min return	-9,44%	-9,44%	-7,89%	-9,38%	-9,41%	-7,40%	-7,33%
Max Drawdown	-33,11%	-29,75%	-29,38%	-29,64%	-29,70%	-27,11%	-38,41%
ESG quality score from MSCI	A (6.94)	A (7.04)	A (6.91)	AA (7.74)	AA (7.24)	AA (7.82)	AA (7.83)

The summary statistics table summarizes all the metrics for each strategy created to provide a better method for comparing all of them with the BPI Opportunities.

10. Limitations

While findings in this paper are highly relevant, some limitations were found throughout the project. Presenting the limitations contributes to a better understanding of the results and the value-added of the research. Firstly, the inception date of BPI Opportunities dates back to November 2018, hence, the real fund data was only studied for 3 years. To provide more robust analysis, with a longer time period, a backtest was computed from October 2003 to November 2018, and it was added to the real portfolio data, which ranges from inception up to the present. This backtest does not properly replicate the current quality strategy, as it evolved over time – thus, this can impact the regression results presented in Section 7. To overcome this challenge, when incorporating new strategies to improve the current quality model (Section 9), a real backtest of the current strategy was computed.

The second challenge encountered was the currency conversion of the factors' returns. In order to analyse BPI fund returns from a European investor's perspective, the returns of the factor models had to be converted to euros. There is no bullet-proof methodology to properly convert factor returns, therefore the methodology suggested by (Glück, Hübel, and Scholz, 2020), was the one this paper resorted to. An additional challenge was faced when converting Bloomberg factors. These factors are first built for each country, being expressed in the local currency, and then converted to global factors through a weighted average of the country-specific factors. As a result, the returns are not provided in a single currency but rather as a weighted average of the different local currencies. In the absence of an exchange rate that takes this "mixed currency" into account, there is no precise and accurate way of performing the conversion to euros. Thus, this paper resorted to the USD/EUR exchange rate, given that the US is the country with the largest representativity on Bloomberg factors' construction.

Regarding the macroeconomic analysis, presented in Section 6, there were not enough global macroeconomic variables to perform the analysis, plus the ones found did not provide sufficient historical data. In the absence of appropriate global variables, the solution was to use U.S. macroeconomic data as a proxy for global data, since it represents the largest share of the geographic allocation of BPI Opportunities and also because the U.S. is the world's largest economy, with a high level of contagion overseas.

11. Further research

Considering the findings and limitations of the research, we propose a few areas for further investigation to achieve the ultimate "decoding" of quality: (1) extend the macroeconomic analysis to other geographies to check to which trends the performance of quality obeys, and apply machine learning techniques to adapt quality metrics to different macroeconomic contexts and region-specific trends; (2) improve the understanding of the drivers of quality using techniques such as Principal Component Analysis to recognize which features explain the most variance in the cross-section of quality returns; (3) explore other multifactor strategies using the combination of quality with other risk factors.

Moreover, from an operational standpoint and to improve BPI GA's quality strategy it is recommended that BPI GA: (1) expands the empirical analysis to other funds that replicate the quality strategy in different geographies (such as BPI Europa, BPI America, and BPI Asia Pacific); (2) uses SABS Materiality Map to account for ESG materiality; (3) extends the backtest of BPI Opportunities using a higher time horizon (30-40 years), assuming the factor loadings that the strategy yielded for the true sample period (~3 years) and joint sample period (~20 years), to get a bigger picture of how the strategy might have performed over a long sample period and also, how the factor returns might have behaved in the past (to test premia consistency).

12. Conclusions

Quality is defined as a set of competitive characteristics that investors should be willing to pay a premium for. Nevertheless, empirical evidence indicates that the quality premium is not completely priced in. Therefore, quality companies appear to generate excess returns.

This paper set out to analyse BPI Opportunities interaction with the quality anomaly and improve BPI GA's quality investment strategy by extending it to other dimensions. The base assumption of this paper is BPI Opportunities exposure to the quality premium. Hence, robustness tests and regression analyses on BPI Opportunities were run to confirm the exposure and the validity of internally used factor models.

Tests on BPI Opportunities and style indices suggest that AQR, Fama-French and Bloomberg factors are suitable to explain BPI Opportunities returns. While the robustness tests suggest the validity of all models analysed, the conversion of the Bloomberg factors using the USD/EUR exchange rate leads to a significant decrease in R-squared. This is likely related to the “mixed currency” nature of the Bloomberg factor returns and hints to possible issues with the model. Hence, BPI GA may consider extending its factor analysis with factors from the other two data providers to ensure more reliable regression results moving forward.

Analysing BPI Opportunities factor exposure, AQR and Fama-French factors suggest significant exposure to the quality factors across the two sample periods, while Bloomberg’s factors indicate exposure to quality-only during the true sample period. Thus, there is evidence that BPI Opportunities has exposure to the quality premium. Moreover, the exposure to the quality factor indicates that – in line with BPI GA’s goal – a significant portion of BPI Opportunities returns are driven by quality.

Following the confirmation of BPI Opportunities exposure to the quality premium, literature was reviewed to investigate the possibility of extending the quality strategy though other dimensions, aiming at improving BPI Opportunities performance. Evidence has shown that (1) quality and value investing styles are good compliments; (2) quality companies tend to have high ESG ratings; (3) long-short outperforms long-only quality strategies across different regions; and (4) the quality premium behavior varies and is contingent on the macroeconomic environment.

Then, the behavior of the quality premium in varying macroeconomic environments was investigated to anticipate the performance of BPI Opportunities in different macro-outlooks. It was found that rising volatility and inflation are linked to a higher quality premium, while rising copper prices, decreasing unemployment rates and higher consumer sentiment – indicators of a positive economic outlook – decrease the premium. Hence, it is recommended that BPI GA pays close attention to these indicators and reduces its quality exposure in times of economic growth, while increasing it in times of volatility and inflation.

Moreover, strategies combining quality and ESG, quality and value, and a long-short quality strategy have been developed. When backtesting these strategies, it was found that:

(1) Extending BPI Opportunities strategy to a value dimension does not improve results. By excluding the 30 worst value companies from a portfolio of the top 80 quality companies - as defined by BPI GA's model - the risk-reward ratio decreases from 1.3 to 1.18. In line with theory, this strategy slightly reduces volatility, however, the observed reduction in returns more than offsets this benefit. Hence, BPI GA should refrain from using this strategy at present. Nevertheless, the risk-reward ratio is good, and the strategy may well become highly effective in an environment with increasing interest rates following inflation. Since the value premium has historically outperformed in high interest rate environments, BPI GA may want to revisit this strategy as central banks start resorting to contractionary monetary policies following inflation;

(2) Long- short quality strategies, going long on the top 50 quality companies and short on the 50 worst junk companies can add value. A 100-100 and a 130-30 long-short quality strategies were tested, whereby the latter exhibits an exceptional risk-reward ratio of 1.37, while the 100-100 strategy exhibits a ratio of 0.59. This difference in returns is likely related to the relative market neutrality of the 100-100 strategy. Moreover, the exceptional performance of the 130-30 strategy might be explained by the *de facto* use of 160% of the

portfolio's assets. Nevertheless, the low standard deviation of the strategy is striking and indicates that BPI Opportunities strategy is good at identifying quality and junk companies. Thus, pursuing long-short quality strategies may create value to BPI GA;

(3) Adjusting the weights of BPI Opportunities' holdings based on ESG ratings, results in an improved ESG rating of the portfolio without compromising the portfolio's returns. By assigning a weight of 3% to the holdings in the top tercile of ESG ratings, 2% to the middle tercile and 1% to the bottom tercile, an improvement in the portfolio's ESG rating from A to AA was achieved. Moreover, the risk-reward ratio increased from 1.3 to 1.31. Hence, there is evidence that BPI Opportunities can improve its ESG rating without sacrificing returns by applying the proposed ESG strategy.

To conclude, BPI Opportunities is exposed to quality in both sample periods, and its quality investing strategy can be improved by extending it to other investment styles and by paying close attention to pivotal macroeconomic indicators identified in this paper. The evidence found in this thesis confirms the hypothesis that extending BPI Opportunities to other dimensions can improve its risk-adjusted returns. However, some of the strategies tested may be difficult to implement for institutional investors with a strict investing mandate.

Hence, it is recommended that BPI GA focuses on those strategies that can be implemented. The authors of this paper recommend the implementation of the ESG tilt strategy. Furthermore, the 130-30 strategy may be worth further investigation as it could be a good addition to BPI GA's long-short strategies currently focusing on the Iberian market. Finally, the quality strategy with the value calibration could also be revisited when interest rates start to rise.

13. Annex

I. Definition of Quality

Annex 1: Quality Definitions

Practitioner / Institution	Quality definition
AQR Capital Management	• Total profits/assets • Gross margins • Free cash flow/assets
Dimensional Fund Advisors	• Operating income before depreciation and amortization minus interest expense scaled by book value
MSCI Quality Indices	• Return on Equity (ROE) • Debt to equity • Earnings variability: Standard deviation of YOY earnings per share growth over last five fiscal years
Piotroski F-score	• Return on assets • Operating - Cash flow • Quality of earnings • Net income • Leverage • Liquidity equity issuance • Gross margins • Asset turnover
Graham (1973)	Adequate size of enterprise, sufficiently strong financial position,
Novy-Marx (2013)	Gross profit/assets
Sloan (1996)	Difference between cash and accounting earnings scaled by assets (earnings quality)
Fama and French (2014)	Operating income before depreciation and amortization minus interest expense scaled by assets

Table of the best-known quality factor definitions.
Sources:
AQR - "A New Core Equity Paradigm, Using Value, Momentum, and Quality to Outperform Markets," AQR White Paper, March 2013
MSCI - "MSCI Quality Indices Methodology," MSCI White Paper, December 2012
DFA - "Dimensional's Growth Portfolios," Dimensional Fund Advisors White Paper
F-Score - Piotroski, J., "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers," Journal of Accounting Research, Vol 38 Supplement, 2000

II. MSCI World indices regressions in dollars (USD)

The dependent variables, for each column are, respectively, MSCI World index, MSCI World Quality index, MSCI World Value index, MSCI World Momentum index, MSCI World Minimum Volatility index. The independent variables are Fama-French factors MKT-RF, SMB, CMA, RMW and HML. Results in USD.

a) MSCI indices on Fama French factors

Sample period: 2000/01/05 – 2021/08/04

Annex 2: MSCI indices on Fama-French Factors (USD)

	Fama-French Global Factors: Robustness tests (USD)				
	World	World Quality	World Value	World Momentum	World Min Vol
const	-0.000***	0.000	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT-RF	0.993***	0.922***	0.989***	0.989***	0.732***
	(0.004)	(0.009)	(0.008)	(0.008)	(0.017)
SMB	-0.178***	-0.301***	-0.265***	-0.265***	-0.105***
	(0.010)	(0.017)	(0.021)	(0.021)	(0.033)
CMA	0.025*	0.100***	0.082***	0.082***	0.317***
	(0.014)	(0.029)	(0.031)	(0.031)	(0.045)
RMW	0.044***	0.391***	-0.068***	-0.068***	0.352***
	(0.011)	(0.029)	(0.025)	(0.025)	(0.036)
HML	0.017*	-0.248***	0.355***	0.355***	-0.061**
	(0.010)	(0.019)	(0.021)	(0.021)	(0.030)
Observations	1,131	1,131	1,131	1,131	1,131
R^2	0.993	0.959	0.975	0.975	0.872
Adjusted R^2	0.993	0.959	0.975	0.975	0.871

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Regressions of MSCI indices excess returns on systematic risk factors using the Fama French 5-Factor Model, over the sample period of 2000/01/05 – 2021/08/04 (USD).

b) MSCI indices on AQR factors

Sample period: 2000/01/05 – 2021/08/04

Annex 3: MSCI indices on AQR Factors (USD)

	AQR Global Factors: Robustness tests (USD)				
	World	World Quality	World Value	World Momentum	World Min Vol
const	-0.000***	-0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT-RF	1.013***	1.037***	0.977***	1.035***	0.750***
	(0.006)	(0.020)	(0.010)	(0.024)	(0.020)
MOM	-0.038***	-0.033***	-0.130***	0.391***	0.004
	(0.006)	(0.011)	(0.011)	(0.020)	(0.015)
SMB	-0.179***	-0.154***	-0.285***	-0.014	-0.177***
	(0.012)	(0.029)	(0.023)	(0.038)	(0.031)
HML	0.007	-0.202***	0.332***	-0.070*	0.131***
	(0.007)	(0.019)	(0.016)	(0.036)	(0.024)
QMJ	0.112***	0.525***	0.069***	0.093*	0.322***
	(0.012)	(0.033)	(0.025)	(0.054)	(0.041)
Observations	1,127	1,127	1,127	1,127	1,127
R^2	0.993	0.948	0.976	0.909	0.867
Adjusted R^2	0.993	0.947	0.976	0.909	0.867

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Regressions of MSCI indices excess returns on systematic risk factors using the AQR 5-Factor Model, over the sample period of 2000/01/05 – 2021/08/04 (USD).

c) MSCI indices on Bloomberg indices
Sample period: 2000/01/05 – 2021/08/04

Annex 4: MSCI indices on Bloomberg Factors (USD)

	Bloomberg Global Factors: Robustness tests (USD)				
	World	World Quality	World Value	World Momentum	World Min Vol
const	-0.000***	0.000**	-0.001***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT-RF	1.014***	0.969***	0.992***	1.026***	0.762***
	(0.006)	(0.012)	(0.015)	(0.018)	(0.021)
Momentum	0.015*	0.171***	-0.329***	1.360***	0.076
	(0.009)	(0.043)	(0.055)	(0.065)	(0.055)
Size	-0.066**	-0.171**	0.215**	-0.709***	-0.350***
	(0.030)	(0.075)	(0.094)	(0.119)	(0.124)
Value	0.006	-0.395***	0.689***	-0.533***	-0.011
	(0.025)	(0.081)	(0.134)	(0.127)	(0.130)
Profit	0.010	0.771***	0.085	0.288*	1.185***
	(0.018)	(0.097)	(0.110)	(0.150)	(0.109)
Observations	1,126	1,126	1,126	1,126	1,126
R^2	0.999	0.941	0.966	0.900	0.879
Adjusted R^2	0.999	0.941	0.966	0.899	0.879
Standard errors in parentheses					*p<0.1; **p<0.05; ***p<0.01

Regressions of MSCI indices excess returns on systematic risk factors using the Bloomberg 5-Factor Model, over the sample period (USD).

III. MSCI World indices regressions in euros (EUR)

The dependent variables, for each column are, respectively, MSCI World index, MSCI World Quality index, MSCI World Value index, MSCI World Momentum index, MSCI World Minimum Volatility index. The independent variables are Fama-French factors MKT-RF, SMB, CMA, RMW and HML. Results in EUR.

a) MSCI indices on Fama-French factors

Sample period: 2000/01/05 – 2021/08/04

Annex 5: MSCI indices on FF Factors (EUR)

	Fama-French Global Factors: Robustness tests (EUR)				
	World	World Quality	World Value	World Momentum	World Min Vol
const	-0.000*	0.000*	-0.000***	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT-RF	0.992***	0.922***	0.988***	0.988***	0.731***
	(0.004)	(0.008)	(0.008)	(0.008)	(0.017)
SMB	-0.179***	-0.302***	-0.265***	-0.265***	-0.105***
	(0.011)	(0.017)	(0.022)	(0.022)	(0.033)
CMA	0.027*	0.102***	0.084***	0.084***	0.318***
	(0.015)	(0.029)	(0.032)	(0.032)	(0.045)
RMW	0.043***	0.391***	-0.070***	-0.070***	0.350***
	(0.011)	(0.029)	(0.025)	(0.025)	(0.036)
HML	0.017*	-0.249***	0.356***	0.356***	-0.061**
	(0.010)	(0.019)	(0.021)	(0.021)	(0.030)
Observations	1,131	1,131	1,131	1,131	1,131
R^2	0.993	0.959	0.975	0.975	0.871
Adjusted R^2	0.993	0.959	0.975	0.975	0.871

Standard errors in parentheses   *p<0.1; **p<0.05; ***p<0.01

Regressions of MSCI indices excess returns on systematic risk factors using the Fama-French 5-Factor Model, over the sample period of 2000/01/05 – 2021/08/04 (EUR).

b) MSCI indices on AQR factors

Sample period: 2000/01/05 – 2021/08/04

Annex 6: MSCI indices on AQR Factors (EUR)

	AQR Global Factors: Robustness tests (EUR)				
	World	World Quality	World Value	World Momentum	World Min Vol
const	-0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT-RF	1.012***	1.036***	0.975***	1.034***	0.748***
	(0.006)	(0.020)	(0.010)	(0.024)	(0.020)
MOM	-0.038***	-0.034***	-0.130***	0.390***	0.003
	(0.006)	(0.011)	(0.011)	(0.020)	(0.015)
SMB	-0.179***	-0.153***	-0.285***	-0.013	-0.176***
	(0.012)	(0.029)	(0.024)	(0.038)	(0.031)
HML	0.007	-0.202***	0.332***	-0.070*	0.130***
	(0.007)	(0.019)	(0.016)	(0.037)	(0.024)
QMJ	0.110***	0.524***	0.068***	0.091*	0.320***
	(0.012)	(0.033)	(0.025)	(0.054)	(0.042)
Observations	1,127	1,127	1,127	1,127	1,127
R^2	0.993	0.948	0.976	0.909	0.866
Adjusted R^2	0.993	0.947	0.976	0.909	0.866

Standard errors in parentheses   *p<0.1; **p<0.05; ***p<0.01

Regressions of MSCI indices excess returns on systematic risk factors using the AQR 5-Factor Model, over the sample period of 2000/01/05 – 2021/08/04 (EUR).

c) MSCI indices on Bloomberg factors

Sample period: 2000/01/05 – 2021/08/04

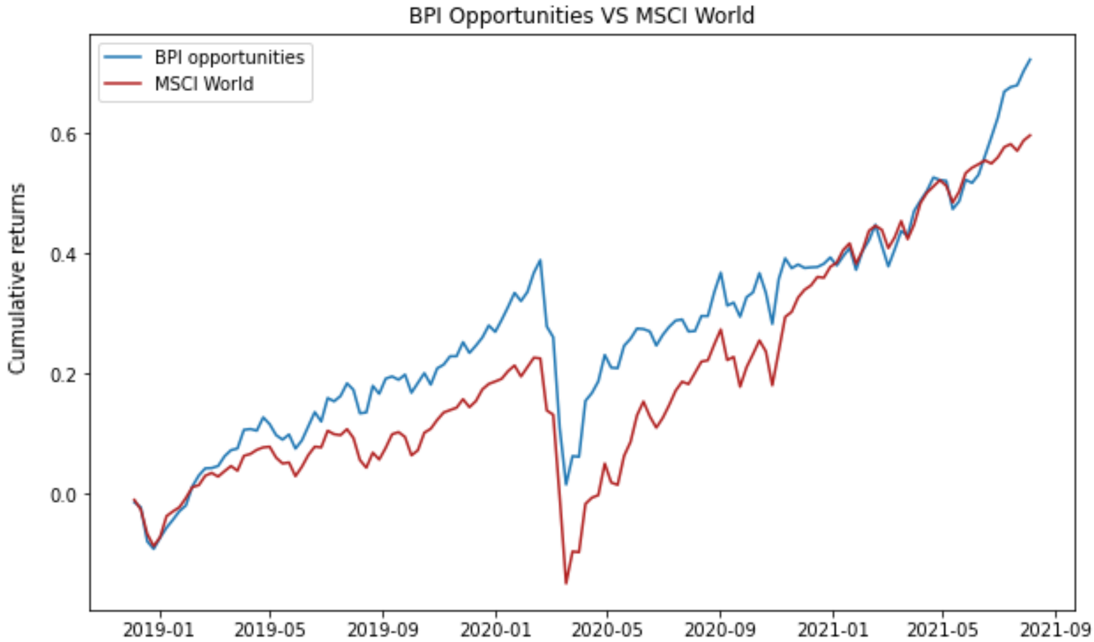
Annex 7: MSCI indices on Bloomberg Factors (EUR)

	Bloomberg Global Factors: Robustness tests (EUR)				
	World	World Quality	World Value	World Momentum	World Min Vol
const	-0.000	0.001	-0.001*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT-RF	0.819***	0.774***	0.796***	1.026***	0.567***
	(0.028)	(0.032)	(0.032)	(0.018)	(0.036)
Momentum	0.059	0.214**	-0.286***	1.360***	0.118
	(0.084)	(0.098)	(0.088)	(0.065)	(0.093)
Size	0.428**	0.325	0.707***	-0.714***	0.144
	(0.198)	(0.213)	(0.225)	(0.118)	(0.224)
Value	0.041	-0.358*	0.724***	-0.523***	0.024
	(0.157)	(0.187)	(0.181)	(0.128)	(0.191)
Profit	-0.707***	0.054	-0.632***	0.300**	0.466**
	(0.199)	(0.230)	(0.220)	(0.150)	(0.223)
Observations	1,126	1,126	1,126	1,126	1,126
R^2	0.776	0.663	0.770	0.899	0.510
Adjusted R^2	0.775	0.662	0.769	0.899	0.508
Standard errors in parentheses					*p<0.1; **p<0.05; ***p<0.01

Regressions of MSCI indices excess returns on systematic risk factors using the Bloomberg 5-Factor Model, over the sample period of 2000/01/05 – 2021/08/04 (EUR).

IV. Cumulative Performance of BPI Opportunities against the benchmark

Annex 8: Cumulative Performance of BPI Opportunities vs MSCI World (True sample)

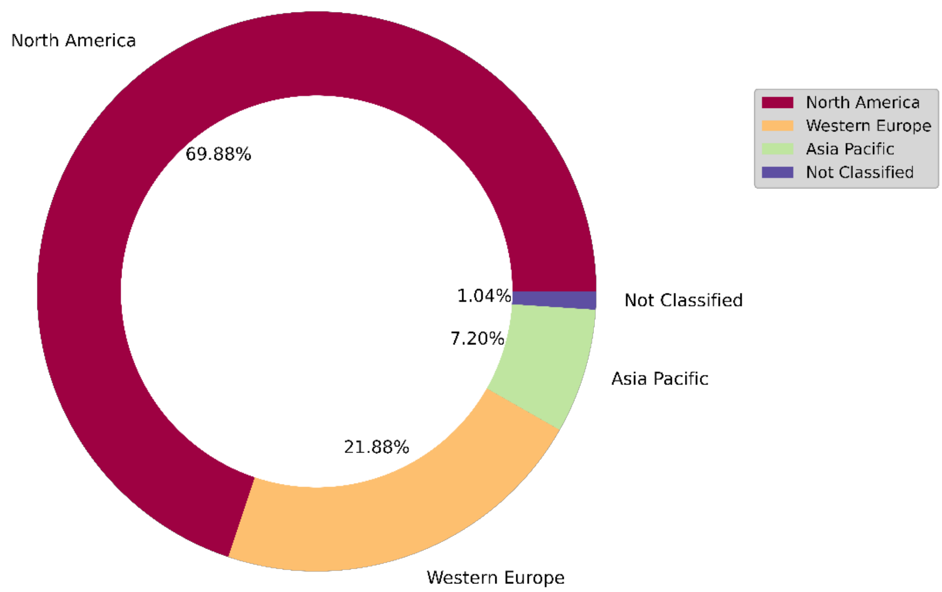


Visualization of BPI Opportunities' cumulative performance since the fund's inception in direct comparison with the benchmark (MSCI World), from December 2018 to September 2021.

V. BPI Geographic Allocation vs Benchmark

a) BPI Opportunities Geographic Allocation

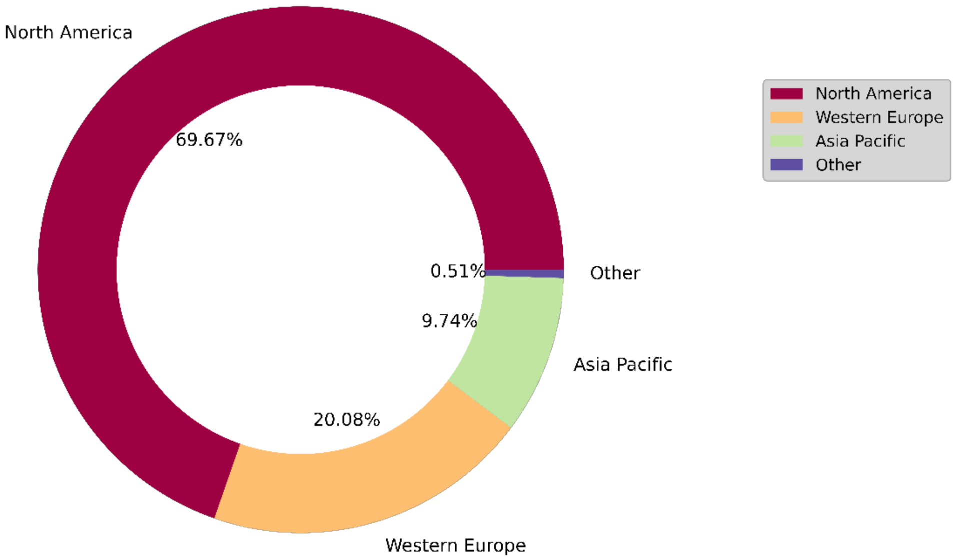
Annex 9: BPI Opportunities Geographic Allocation



The geographical allocation of holdings of BPI Opportunities as of September 2021.

b) MSCI World Index Geographic Allocation

Annex 10: MSCI World Index Geographic Allocation

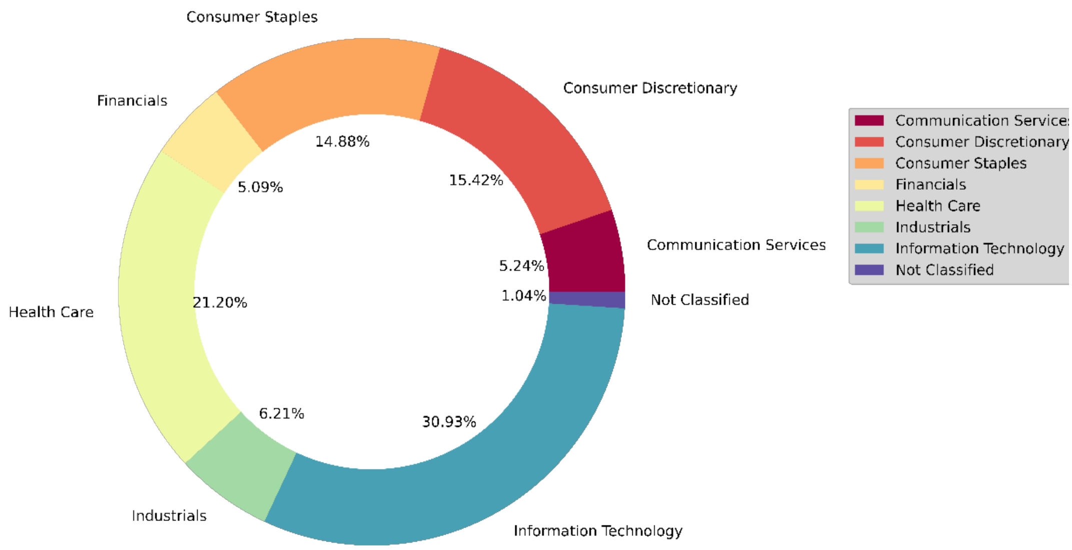


The geographical allocation of holdings of the benchmark (MSCI World Index) as of September 2021.

VI. BPI Sector Allocation vs Benchmark

a) BPI Opportunities Sector Allocation

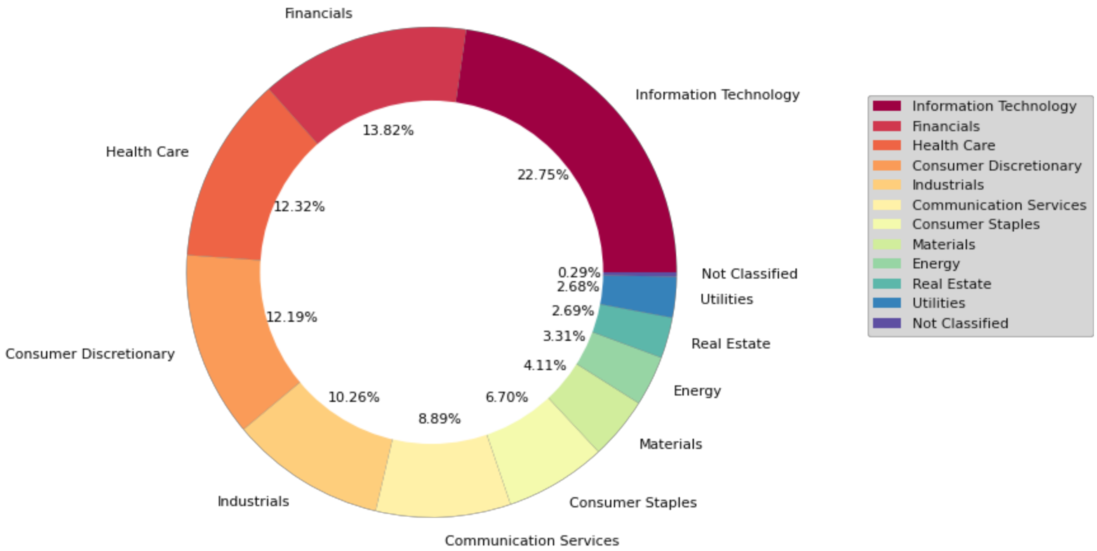
Annex 11: BPI Opportunities Sector Allocation



The sector allocation of holdings of BPI Opportunities as of September 2021.

b) MSCI World Sector Allocation (IWDA NA – BBG Ticker)

Annex 12: MSCI World Sector Allocation

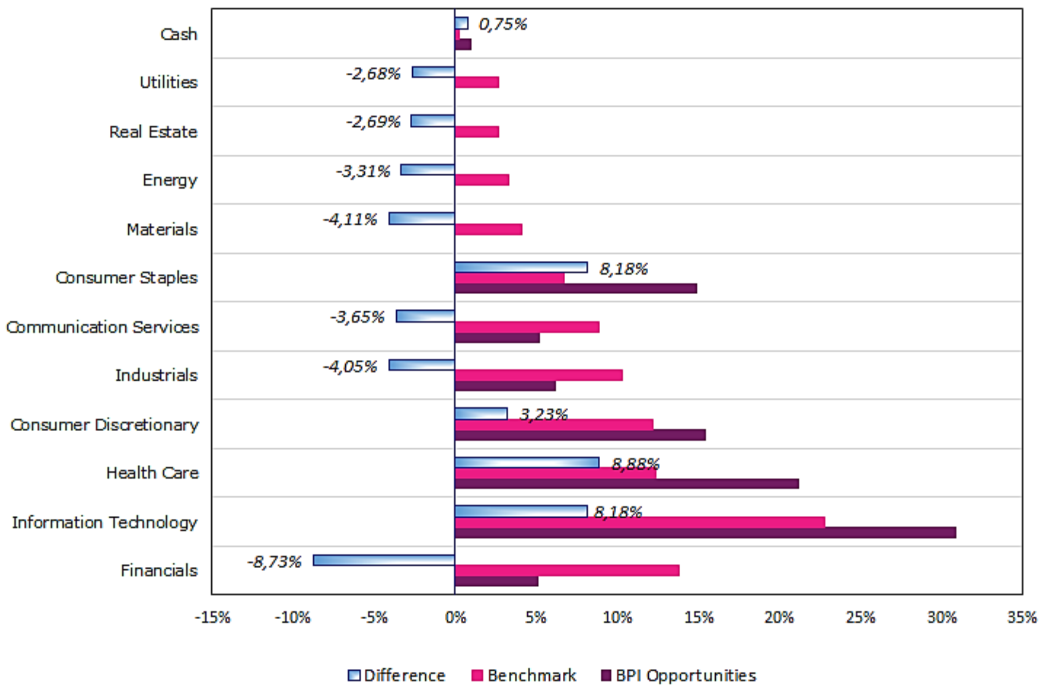


The sector allocation of holdings of the benchmark (MSCI World – IWDA NA) as of September 2021.

c) Difference between sector allocations of BPI Opportunities and MSCI World (2021)

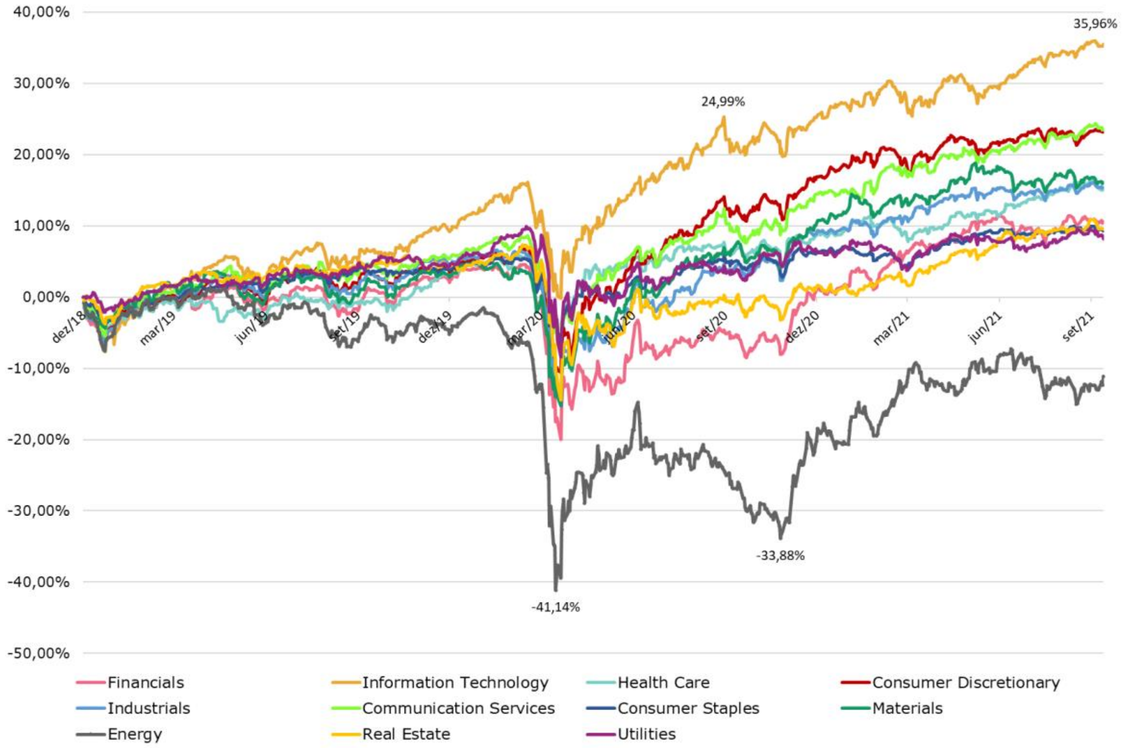
Annex 13: Difference between sector allocations of BPI Opportunities and MSCI World

Sector differences between BPI Opportunities and the benchmark (MSCI World – IWDA NA) as of September 2021.



VII. MSCI World Cumulative Sector Performance

Annex 14: MSCI World Cumulative Sector Performance

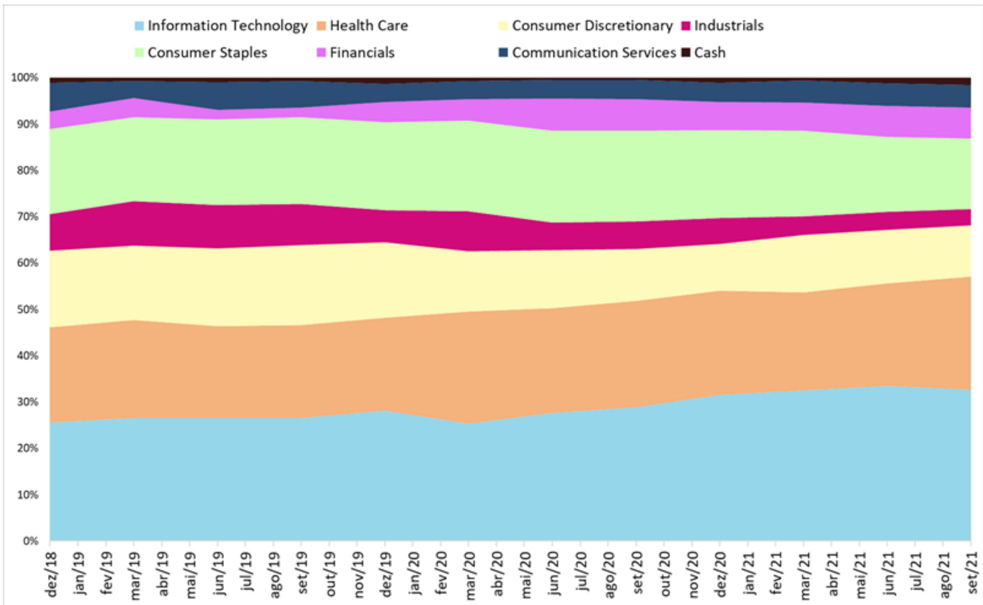


Cumulative performance of MSCI sector indices from December 2018 to September 2021.

VIII. BPI Historical Sector Allocation vs MSCI World Quality ETF

a) BPI Historical Sector Allocation

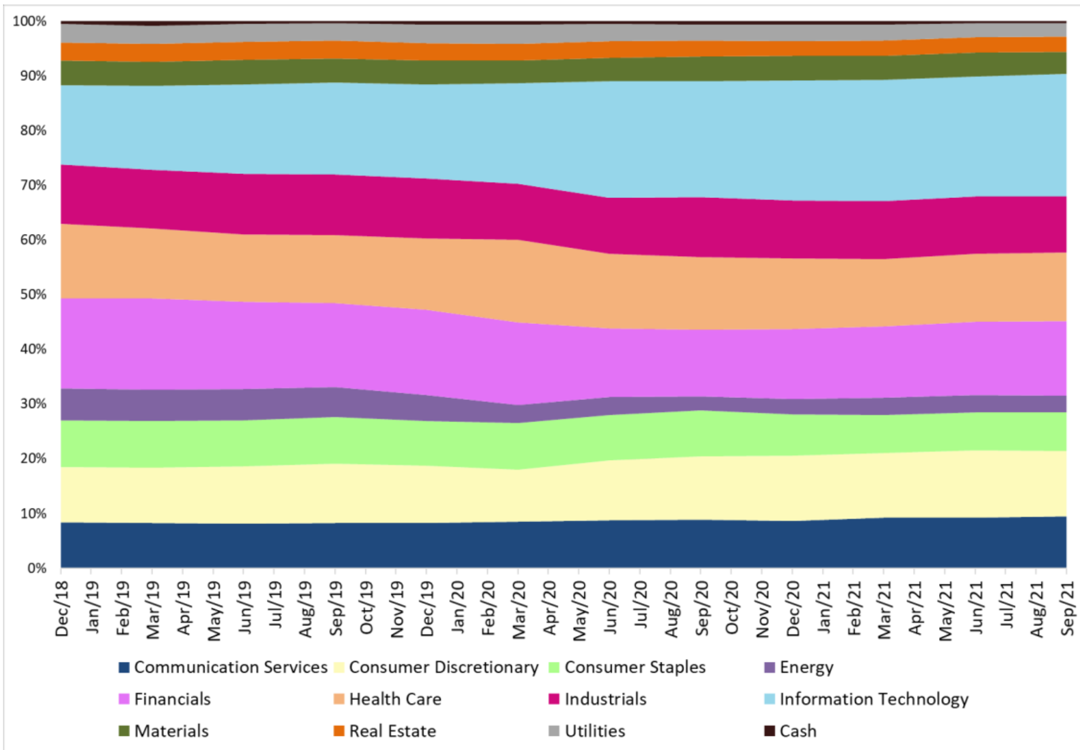
Annex 15: BPI Historical Sector Allocation



BPI Opportunities historical sector allocation since December 2018 to September 2021.

b) MSCI World Quality ETF Historical Sector Allocation

Annex 16: MSCI World Quality ETF Historical Sector Allocation



Historical sector allocation of MSCI World Quality ETF since December 2018 to September 2021.

IX. BPI Performance

a) BPI Opportunities Performance against MSCI World

Annex 17: BPI Opportunities performance against MSCI World

	Total Return (%)			**BPI Opportunities**			
	Port	Bench	+/-	Total Attribution α (%)	Allocation Effect (%)	Selection Effect (%)	Currency Effect (%)
BPI Opportunities	83,44	55,81	27,62	27,62	9,78	18,93	-1,09
Communication Services	5,03	6,13	-1,1	1,63	-0,79	2,10	0,31
Consumer Discretionary	10,15	7,98	2,17	0,91	0,12	0,56	0,24
Consumer Staples	9,52	2,51	7,01	-0,14	-3,67	4,21	-0,69
Energy	0,22	-1,06	1,28	4,43	4,36	0,05	0,02
Financials	6,85	4,57	2,28	7,31	2,86	4,85	-0,39
Health Care	18,71	6,01	12,7	8,27	-0,74	9,01	0,01
Industrials	3,34	5	-1,66	1,75	0,20	1,55	0,00
Information Technology	29,91	20,37	9,54	1,85	5,77	-3,01	-0,91
Materials	0,08	2,55	-2,47	0,25	0,15	-0,01	0,11
Real Estate	0	0,84	-0,84	0,99	0,82	0,00	0,16
Utilities	0	0,92	-0,92	1,15	1,00	0,00	0,15
Not Classified	-0,47	0	-0,47	-0,76	-0,18	-0,38	-0,20
Offset Cash	0,09	0	0,09	-0,03	-0,13	0,00	0,11

Comparison of the performance of BPI Opportunities with the MSCI World ETF with a breakdown of returns by sector. Furthermore, listing of the performance differences due to the allocation effect, the selection effect, and the currency effect. Created by using the Bloomberg PORT function.

b) BPI Opportunities Performance against MSCI World Quality

Annex 18: BPI Opportunities performance against MSCI World Quality

	Total Return (%)			BPI Opportunities			
	Port	Bench	+/-	Total Attribution α (%)	Allocation Effect (%)	Selection Effect (%)	Currency Effect (%)
BPI Opportunities	83,44	61,67	21,76	21,76	4,78	17,64	-0,66
Communication Services	127,2	114,64	12,56	-1,39	-2,20	0,37	0,44
Consumer Discretionary	73,03	70,68	2,35	0,70	0,02	0,52	0,17
Consumer Staples	47,86	21,46	26,4	0,03	-5,65	6,29	-0,61
Energy	-98,75	-9,44	-89,31	4,72	4,47	0,15	0,10
Financials	162,14	57,22	104,91	4,33	0,85	3,80	-0,32
Health Care	84,9	44,34	40,56	7,66	-1,16	8,99	-0,17
Industrials	57,18	51,39	5,8	1,21	0,21	1,00	0,00
Information Technology	110,7	125,08	-14,39	1,74	5,47	-3,06	-0,67
Materials	1,75	59,73	-57,97	0,35	0,21	0,01	0,13
Real Estate	1,2	48,91	-47,71	0,63	0,42	0,00	0,21
Utilities	0,96	0,87	0,1	2,60	2,46	0,00	0,13
Not Classified	-5,03	-2,6	-2,43	-0,83	-0,23	-0,42	-0,18
Offset Cash	-1,26	-0,09	-1,17	0,02	-0,09	0,00	0,11

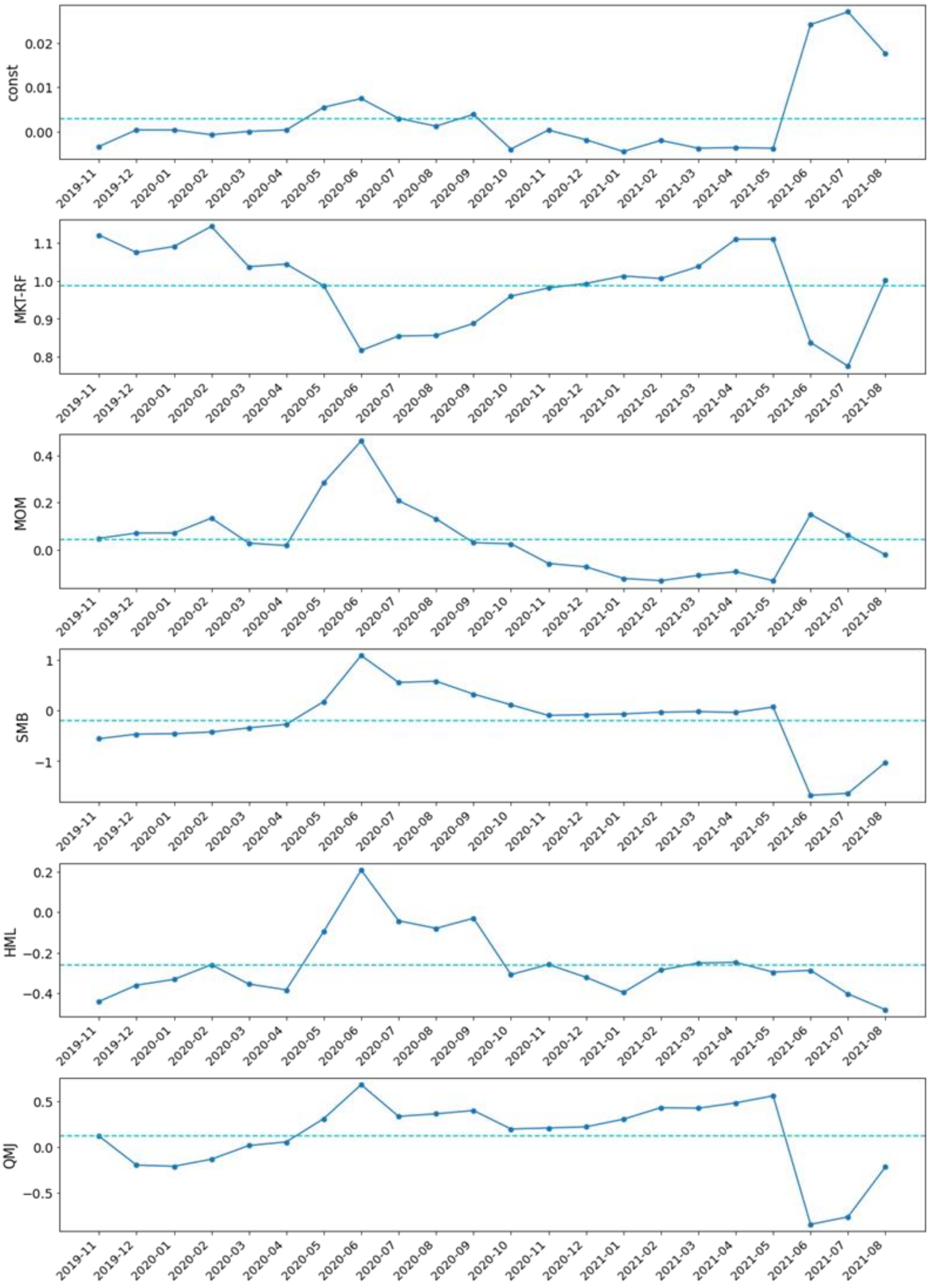
Comparison of the performance of BPI Opportunities with the MSCI World Quality ETF with a breakdown of returns by sector. Furthermore, listing of the performance differences due to the allocation effect, the selection effect and the currency effect. Created by using the Bloomberg PORT function.

X. Rolling regressions

a) Rolling regressions of BPI opportunities on AQR global factors

True Sample Period – 1Y window

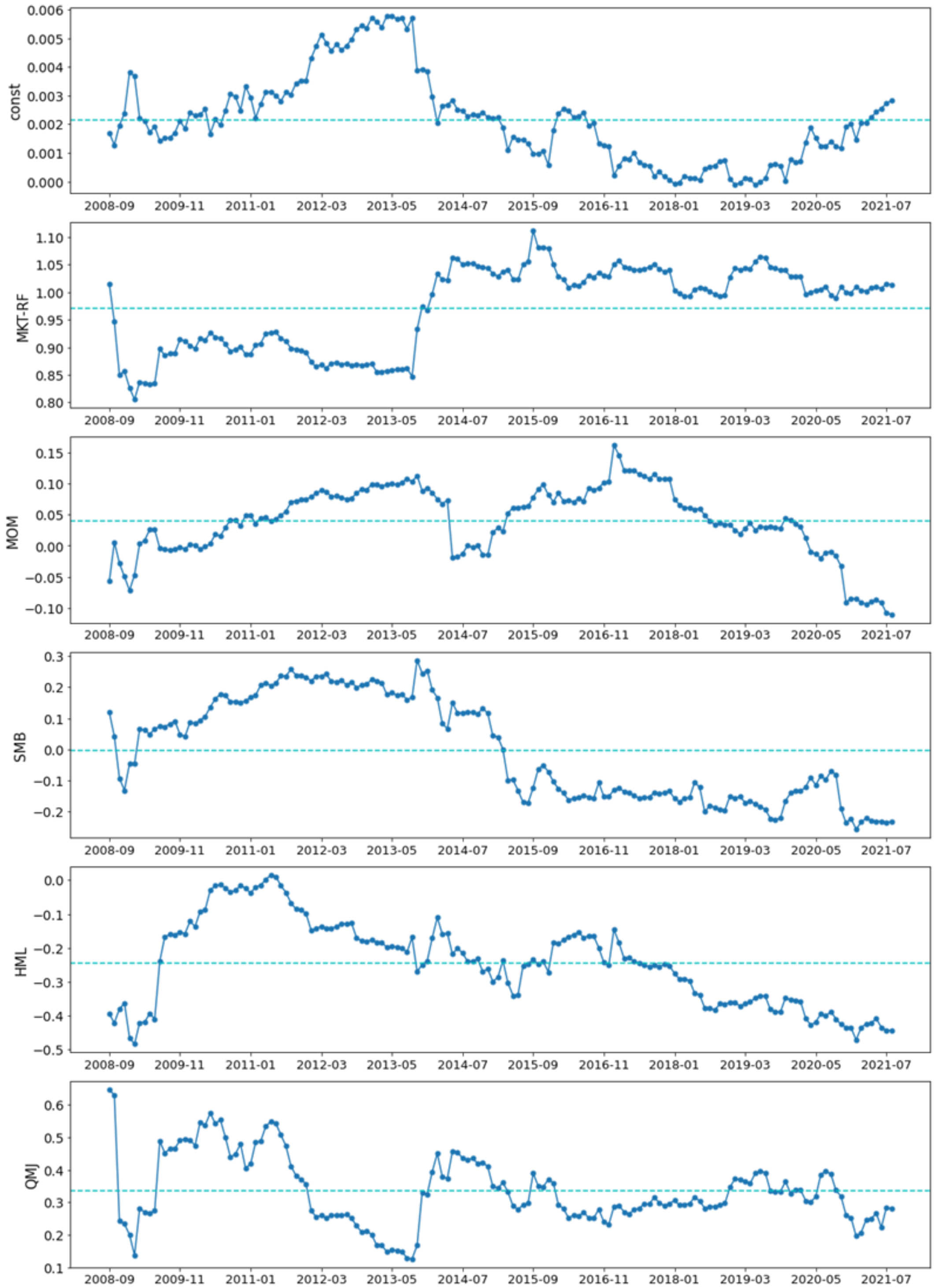
Annex 19: Rolling regressions (AQR, True Sample period)



Using a 1Y window, we do not look at significance due to the small number of observations (12 months). All the dates presented in the graph represent the ending date for the rolling period. That is, the first observation represents the rolling regression coefficient that results from a period that starts in 11/2018 and ends in 11/2019.The average coefficient of exposure is positive for all factors except for value and size. In general, the coefficients peaked in the rolling regressions that end in the period between 06/2020 and 10/2020. For the last dates, coefficients decreased, explaining the increase in alpha.

Joint Sample Period – 5Y window

Annex 20: Rolling Regressions (AQR, Joint Sample Period)

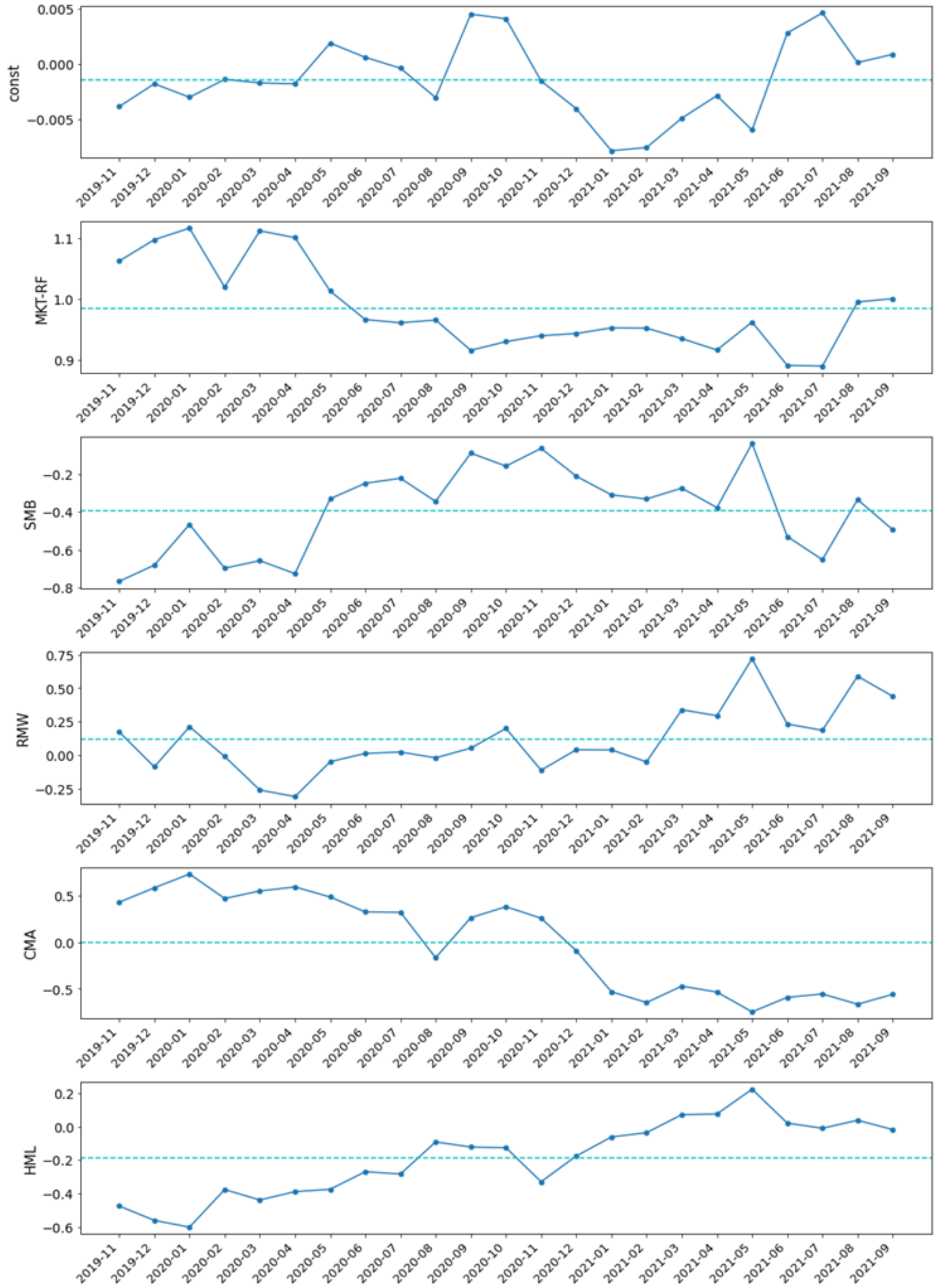


Using a 5Y window, we do not look at significance due to the small number of observations (60 months). All the dates presented in the graph represent the ending date for the rolling period. That is, the first observation represents the rolling regression coefficient that results from a period that starts in 09/2003 and ends in 09/2008. Alpha, MKT-RF, MOM, and QMJ have a positive mean value, while SMB is null and HML is negative. For all coefficients, there was a trend reversal to 09/2013, where all (except MOM) increased from a low to their peak in 12/2014. MOM behaved in the opposite way. Moreover, all coefficients (except MKT-RF and alpha) bottomed out at the end of the joint period.

b) Rolling regressions of BPI opportunities on Fama-French Developed Factors

True Sample Period – 1Y window

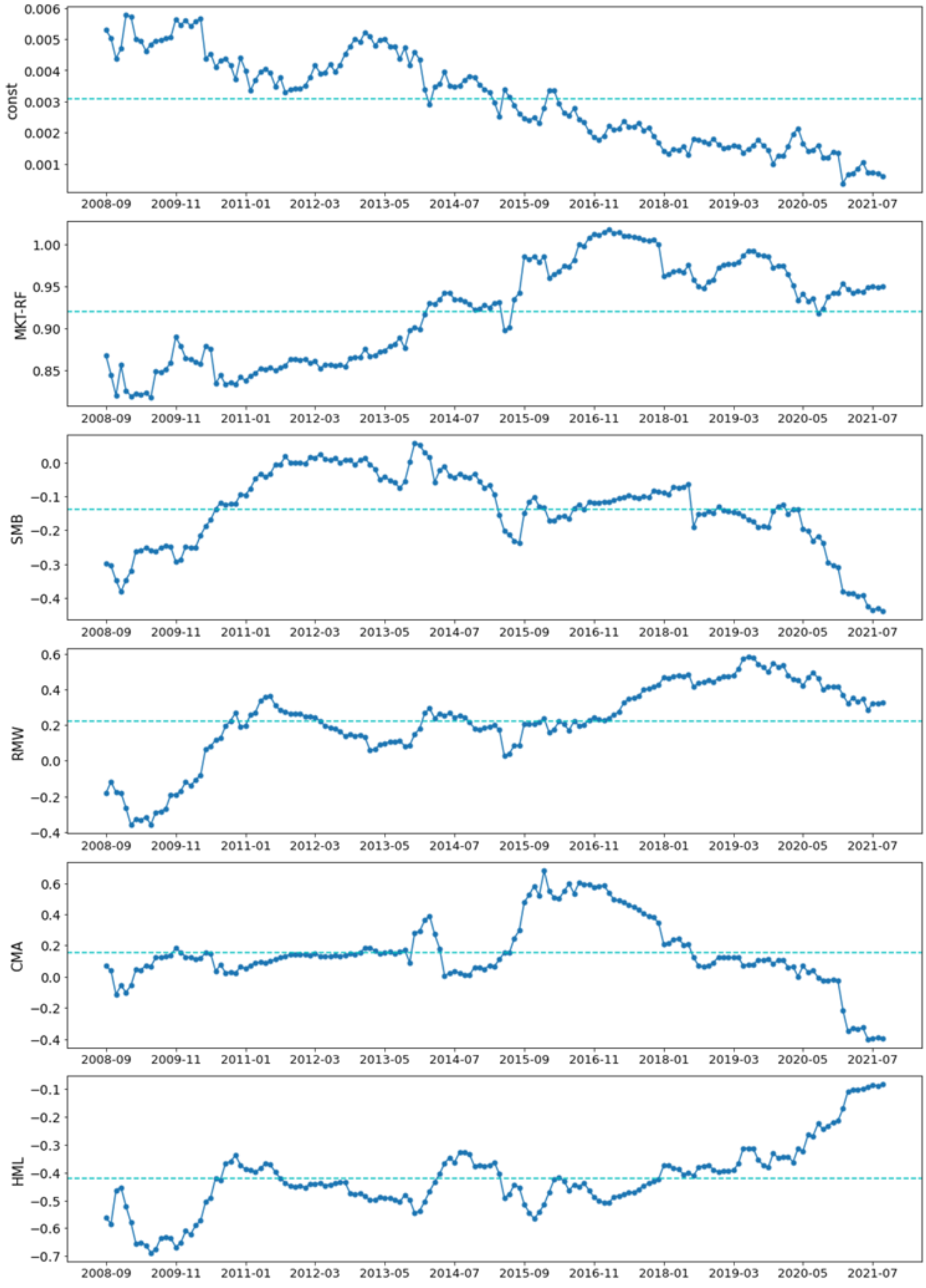
Annex 21: Rolling regressions (FF, True Sample period)



Using a 1Y window, we do not look at significance due to the small number of observations (12 months). All the dates presented in the graph represent the ending date for the rolling period. That is, the first observation represents the rolling regression coefficient that results from a period that starts in 11/2018 and ends in 11/2019. The average coefficient of exposure is positive for MKT-RF and RMW, negative for alpha, RMW and SMB, and null for CMA. As we used RMW (proxy for profitability) and CMA (proxy for leverage) as a proxy for quality, this shows that BPI Opportunities is more exposed to profitability measurements than leverage measurements. This goes in line with the regression we did for Fama-French factors. CMA behaves mirrored to HML, which is an indication of the negative correlation between Value (HML) and Quality (CMA as proxy).

Joint sample period – 5Y window

Annex 22: Rolling regressions (FF, Joint Sample period)

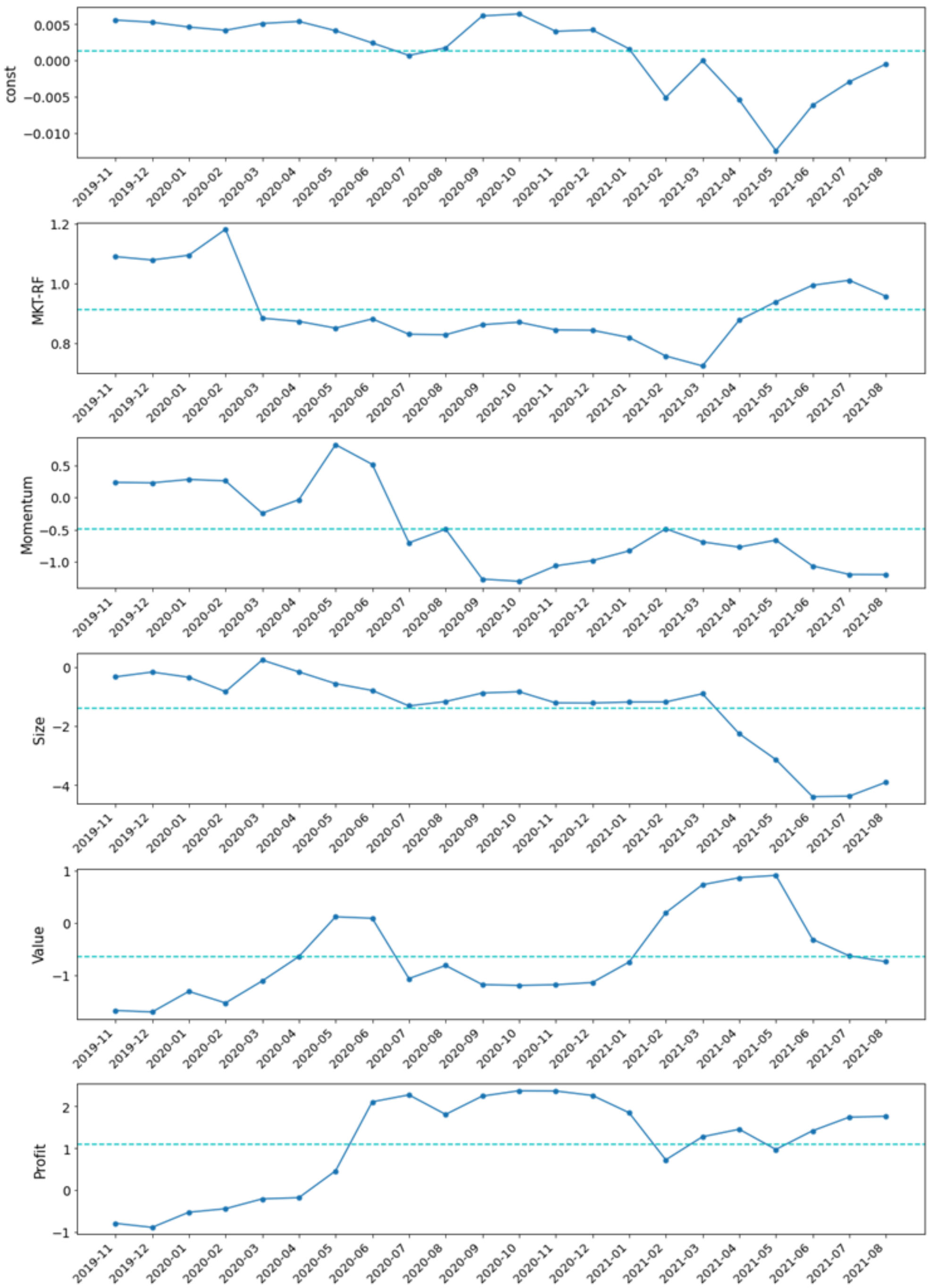


Using a 5Y window, we do not look at significance due to the small number of observations (60 months). All the dates presented in the graph represent the ending date for the rolling period. That is, the first observation represents the rolling regression coefficient that results from a period that starts in 09/2003 and ends in 09/2008. We can observe that HML and RMW have been increasing over time, while alpha has been shrunk. All coefficients have positive mean values except for SMB and HML, which is negatively correlated to quality – the main focus of BPI Opportunities. Over time, the exposure to small caps decreased, the market exposure converged to 1 and the exposure to one of our quality proxies, RMW, increased.

c) Rolling regressions of BPI Opportunities on Bloomberg Global Factors

True Sample Period – 1Y window

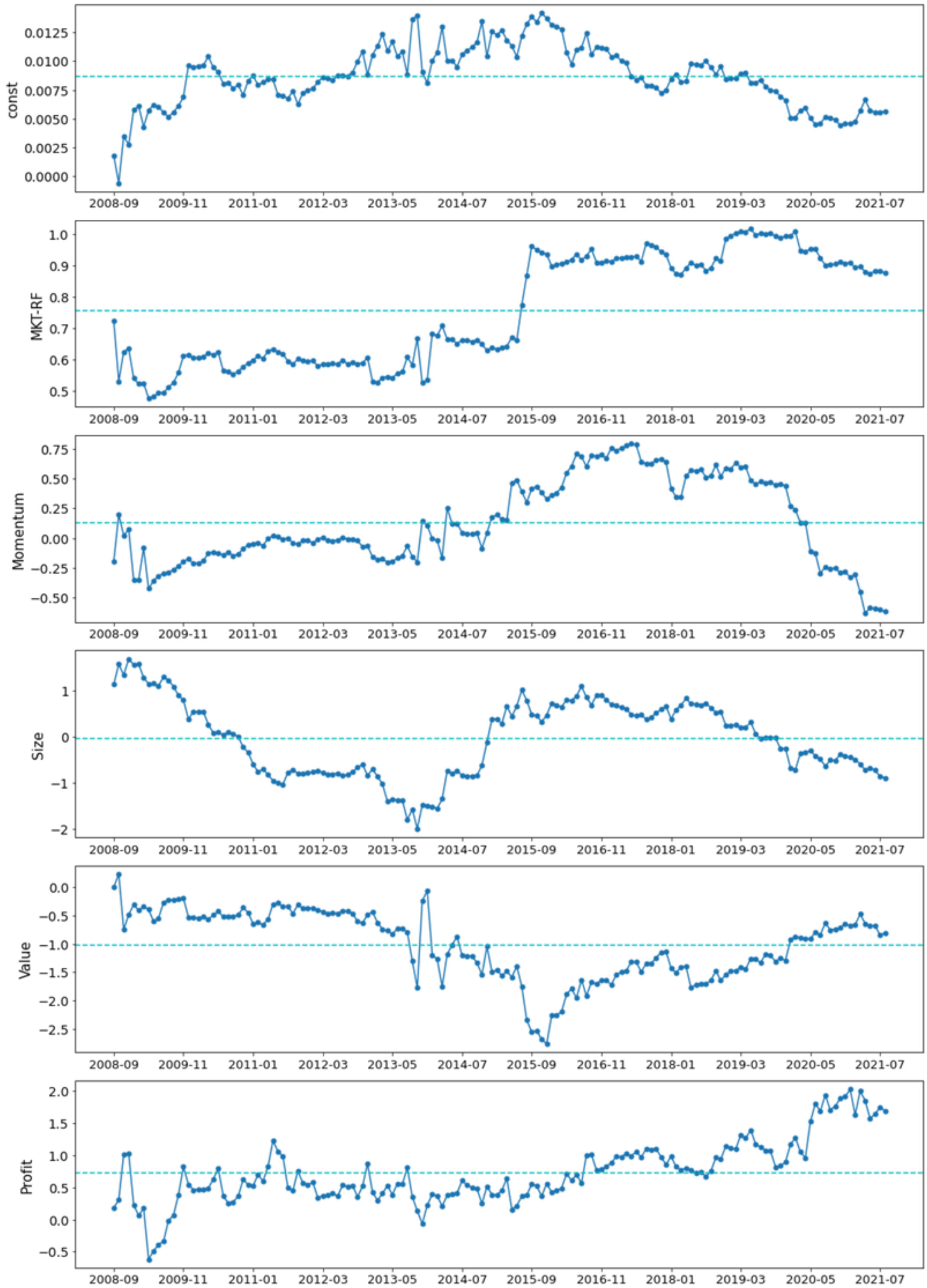
Annex 23: Rolling regressions (BL, True Sample period)



*Using a 1Y window, we do not look at s*ignificance due to the small number of observations (12 months). All the dates presented in the graph represent the ending date for the rolling period. That is, the first observation represents the rolling regression coefficient that results from a period that starts in 09/2018 and ends in 11/2019. The average coefficient of exposure is positive for MKT-RF and Profit, and negative for Size, Momentum and Value, whereas alpha is nearly zero. Coefficient of exposure to Profit (as a proxy for Quality) has increased significantly over time.

Joint Sample Period – 5Y window

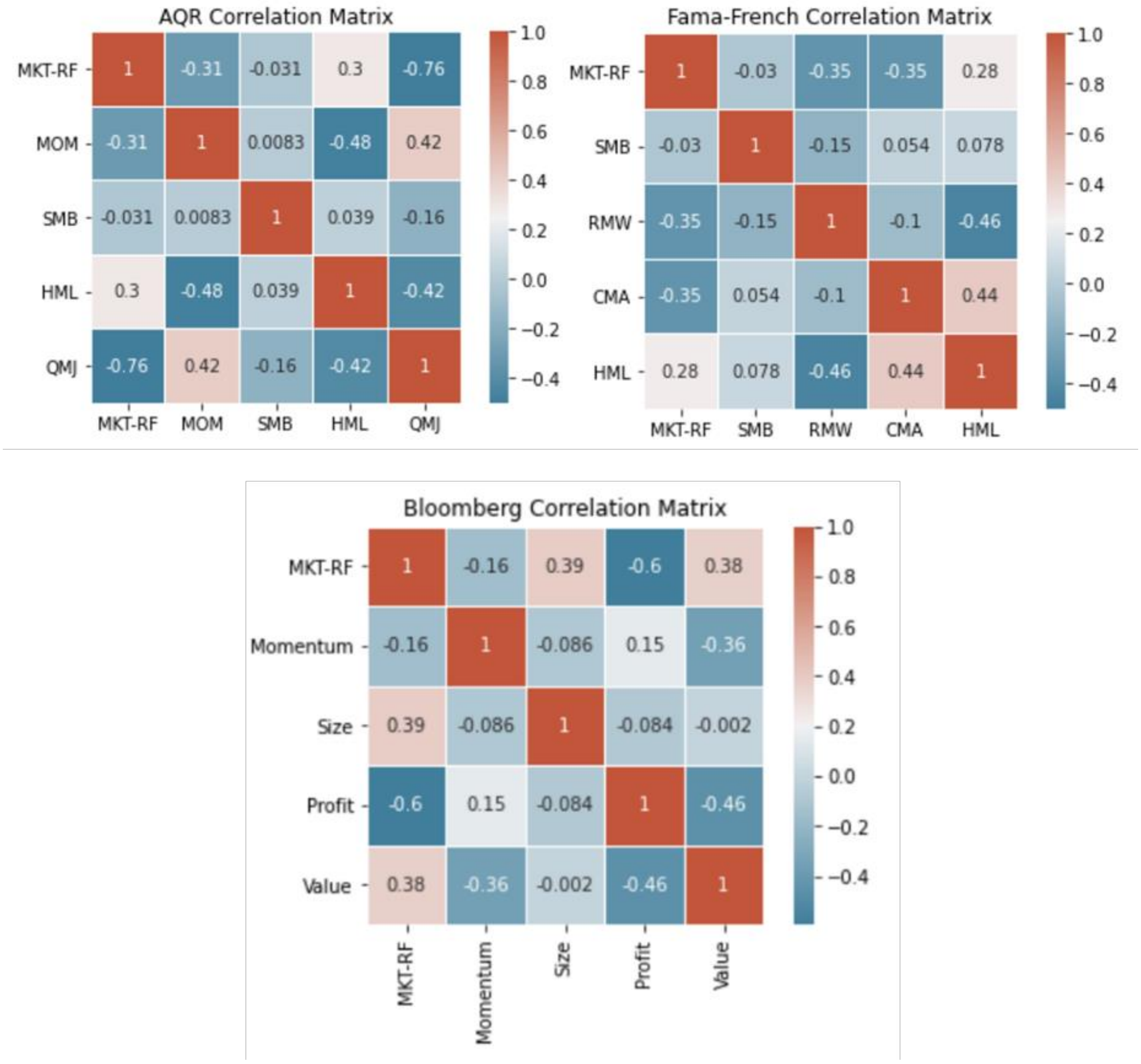
Annex 24: Rolling regressions (BL, Joint Sample period)



*Using a 5Y window, we do not look at significance due to the small number of observations (60 months). All th*e dates presented in the graph represent the ending date for the rolling period. That is, the first observation represents the rolling regression coefficient that results from a period that starts in 09/2003 and ends in 09/2008. Alpha, MKT-RF, Momentum, and Profit have a positive mean value, while Size is null and Value is negative. Value and Size started the period by decreasing and rebounding in mid-2015, whereas the other coefficients increased slowly since the beginning of the period.

XI. Correlation matrix Correlation matrix for factors (Joint Sample)

Annex 25: Factor correlations



Display of all correlation matrices between the respective factors of all three factor models used (Fama-French, AQR, and Bloomberg).

XII. Omitted variable bias

True model:

$R_{BPI} - r_f = \beta_0 + \beta_1$ *(MKT-RF) $+ \beta_2$ (QMJ) $+ \beta_3 \ldots + \beta_4 \ldots + \beta_5 \ldots. + u$, where $+\beta_2 > 0$

CAPM model:

$R_{BPI} - r_f = \widehat{\beta_1}$ *(MKT-RF) $+ u$

QMJ as a function of the MKT-RF:

$QMJ - r_f = \delta_0 + \delta_1$ *(MKT-RF) $+\delta_2 \ldots + \delta_3 \ldots + v$, where $\delta_1 < 0$

CAPM model re-visited:

$R_{BPI} - r_f = \beta_0 + \beta_2 . \delta_0 + (\beta_1 + \beta_2 . \delta_1)$. (MKT-RF) $+ \ldots\ldots. + (u + \beta_2)$,

where $\beta_1, \beta_2 > 0$ and $\delta_1 < 0 \rightarrow = \widehat{\beta_1} = \beta_1 + \boldsymbol{\beta_2 . \delta_1} < \beta_1$ as $\boldsymbol{\beta_2 . \delta_1} < \mathbf{0}$

XIII. Correlation matrix for macroeconomic variables

Annex 26: Macroeconomic correlation matrix

Correlation matrix of all six macroeconomic variables considered.

XIV. Regressions of BPI opportunities on the factor models plus ESG factor

a) BPI opportunities on Fama-French 5 factor model plus ESG factor

Sample period: 2007/02/28 – 2019/03/31

Annex 27: ESG regression (FF Factors)

	Fama-French model plus ESG EW Factor		
	CAPM	5-Factor	6-Factor w/ESG
const	0.005***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
MKT-RF	0.817***	0.917***	0.917***
	(0.023)	(0.025)	(0.025)
SMB		-0.088	-0.098
		(0.070)	(0.071)
CMA		0.218**	0.231**
		(0.090)	(0.092)
RMW		0.258**	0.260**
		(0.108)	(0.108)
HML		-0.477***	-0.489***
		(0.073)	(0.076)
ESG factor EW			-0.050
			(0.074)
Observations	146	146	146
R^2	0.895	0.938	0.938
Adjusted R^2	0.894	0.936	0.936
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01	

Regressions of BPI Opportunities excess returns on systematic risk factors using the Fama-French 5-Factor Model and Pedersen's ESG factor, over the period from February 2007 until March 2019.

b) BPI Opportunities on AQR factor model plus ESG factor

Sample period: 2007/02/28 – 2019/03/31

Annex 28: ESG regression (AQR Factors)

	AQR model plus ESG EW Factor		
	CAPM	5-Factor	6-Factor w/ESG
const	0.006***	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
MKT-RF	0.798***	0.945***	0.951***
	(0.024)	(0.036)	(0.037)
MOM		0.060*	0.062*
		(0.033)	(0.033)
SMB		0.048	0.023
		(0.082)	(0.084)
HML		-0.229***	-0.236***
		(0.076)	(0.076)
QMJ		0.332***	0.361***
		(0.105)	(0.107)
ESG factor EW			-0.111
			(0.090)
Observations	146	146	146
R^2	0.883	0.919	0.919
Adjusted R^2	0.883	0.916	0.916
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01	

Regressions of BPI Opportunities excess returns on systematic risk factors using the AQR 5-Factor Model and Pedersen's ESG factor, over the period from February 2007until March 2019.

c) BPI Opportunities on Bloomberg factor model plus ESG factor

Sample period: 2007/02/28 – 2019/03/31

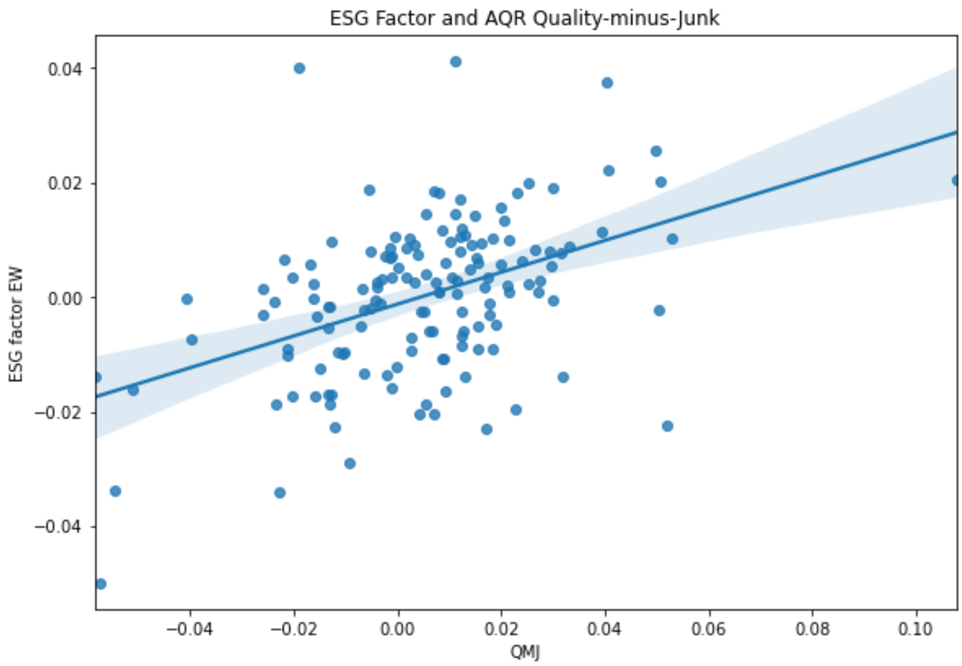
Annex 29: ESG regression (BL Factors)

	Bloomberg model plus ESG EW Factor		
	CAPM	5-Factor	6-Factor w/ESG
const	0.007***	0.009***	0.010***
	(0.002)	(0.003)	(0.003)
MKT-RF	0.597***	0.727***	0.710***
	(0.046)	(0.068)	(0.081)
Momentum		0.037	0.101
		(0.227)	(0.202)
Size		-0.647	-0.319
		(0.579)	(0.613)
Value		-0.833	-0.837*
		(0.506)	(0.508)
Profit		1.023	1.170*
		(0.706)	(0.617)
ESG factor EW			-0.378*
			(0.193)
Observations	146	146	146
R^2	0.535	0.562	0.575
Adjusted R^2	0.531	0.546	0.557
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01	

Regressions of BPI Opportunities excess returns on systematic risk factors using the Bloomberg 5-Factor Model and Pedersen's ESG factor, over the period from February 2007 until March 2019.

XV. ESG factor and AQR Quality Minus Junk factor

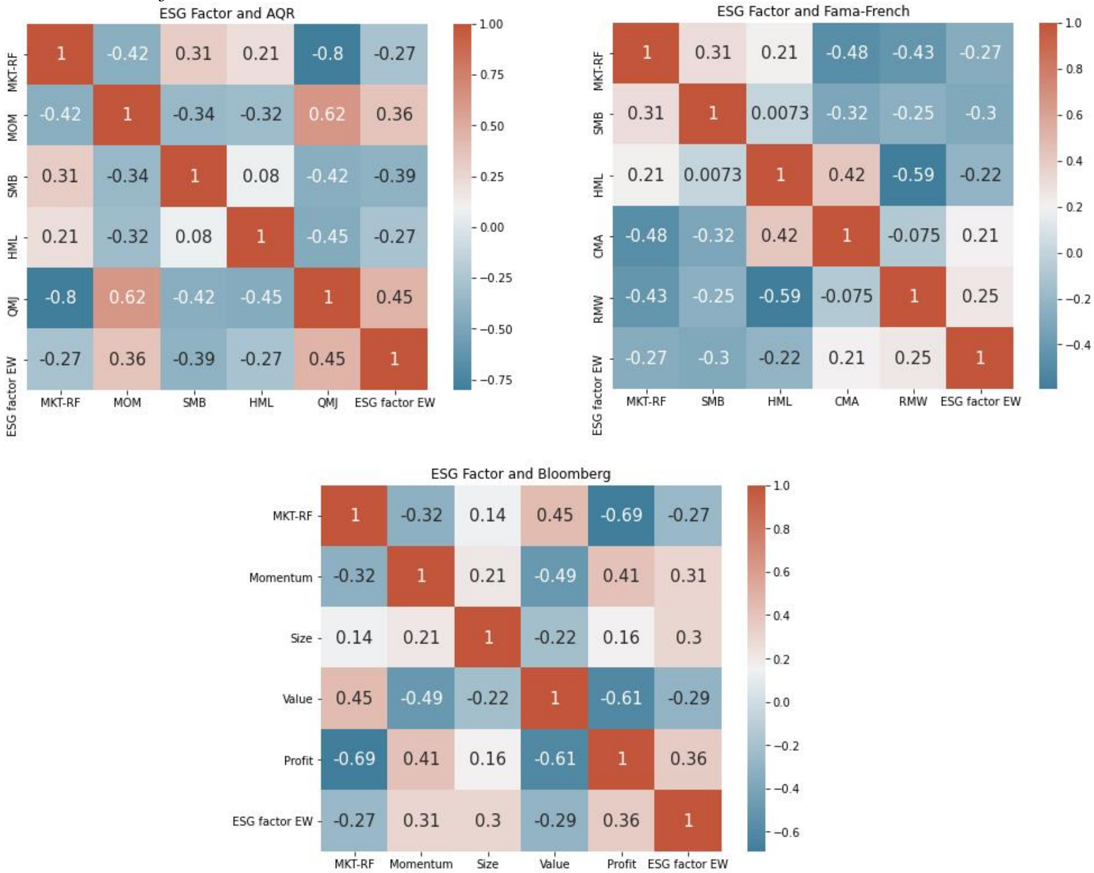
Annex 30: ESG Factor vs QMJ



This scatter plot describes the relationship between the QMJ Factor from AQR and the Pedersen's ESG Factor EW for the period of February 2007 until March 2019.

XVI. Correlation matrices – ESG factor

Annex 31 ESG factor correlation matrices



Display of all correlation matrices between the respective factors of all three factor models used including Pedersen's ESG factor (Fama French, AQR, and Bloomberg).

XVII. Regressions of the new strategies Quality-only, Quality-Value, ESG tilt 0.5, ESG tilt 1, Long-short 100-100, Long-short 130-30 on AQR factor model

a) AQR factor model

Backtest period: 2011/12/31 – 2021/09/30

Annex 32: AQR factors regressions

	Investment strategies with AQR factors					
	Quality	Value	ESG 2,5;2;1,5	ESG 3;2;1	LS 100-100	LS 130-30
const	0.000**	0.000*	0.000**	0.000**	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT-RF	0.984***	0.937***	0.980***	0.977***	0.209***	0.872***
	(0.020)	(0.016)	(0.021)	(0.021)	(0.033)	(0.016)
MOM	0.048*	0.002	0.046*	0.045*	0.166***	0.114***
	(0.025)	(0.022)	(0.024)	(0.024)	(0.062)	(0.021)
SMB	-0.027	-0.097***	-0.052	-0.077**	0.273***	0.123***
	(0.037)	(0.036)	(0.037)	(0.037)	(0.066)	(0.040)
HML	-0.462***	-0.257***	-0.456***	-0.449***	-0.437***	-0.528***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.059)	(0.035)
QMJ	0.172***	0.276***	0.173***	0.174***	0.521***	0.241***
	(0.042)	(0.036)	(0.042)	(0.042)	(0.072)	(0.042)
Observations	2,499	2,499	2,499	2,499	2,499	2,499
R^2	0.773	0.770	0.776	0.776	0.153	0.631
Adjusted R^2	0.772	0.769	0.775	0.775	0.151	0.631

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Regressions of excess returns of the strategies created on systematic risk factors using the AQR 5-Factor Model, over the period from December 2011 until September 2021.

b) Bloomberg factor model

Backtest period: 2011/12/31 – 2021/09/30

Annex 33: BL factors regressions

	Investment Strategies with Bloomberg factors					
	Quality	Value	ESG 2,5;2;1,5	ESG 3;2;1	LS 100-100	LS 130-30
const	0.001	0.001	0.001	0.001*	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MKT-RF	0.832***	0.792***	0.833***	0.833***	0.069	0.783***
	(0.052)	(0.047)	(0.053)	(0.053)	(0.053)	(0.056)
Momentum	1.076***	0.658***	1.038***	1.001***	0.978***	1.505***
	(0.159)	(0.147)	(0.156)	(0.153)	(0.224)	(0.185)
Size	0.469	0.400	0.504*	0.538*	-0.896**	-0.345
	(0.300)	(0.285)	(0.302)	(0.305)	(0.394)	(0.348)
Value	-0.453*	-0.237	-0.482*	-0.510*	0.449	-0.309
	(0.266)	(0.289)	(0.265)	(0.266)	(0.476)	(0.364)
Profit	0.022	0.499*	0.091	0.160	3.400***	1.149***
	(0.328)	(0.259)	(0.323)	(0.320)	(0.448)	(0.385)
Observations	501	501	501	501	501	501
R^2	0.626	0.624	0.629	0.630	0.229	0.503
Adjusted R^2	0.622	0.621	0.625	0.626	0.222	0.498

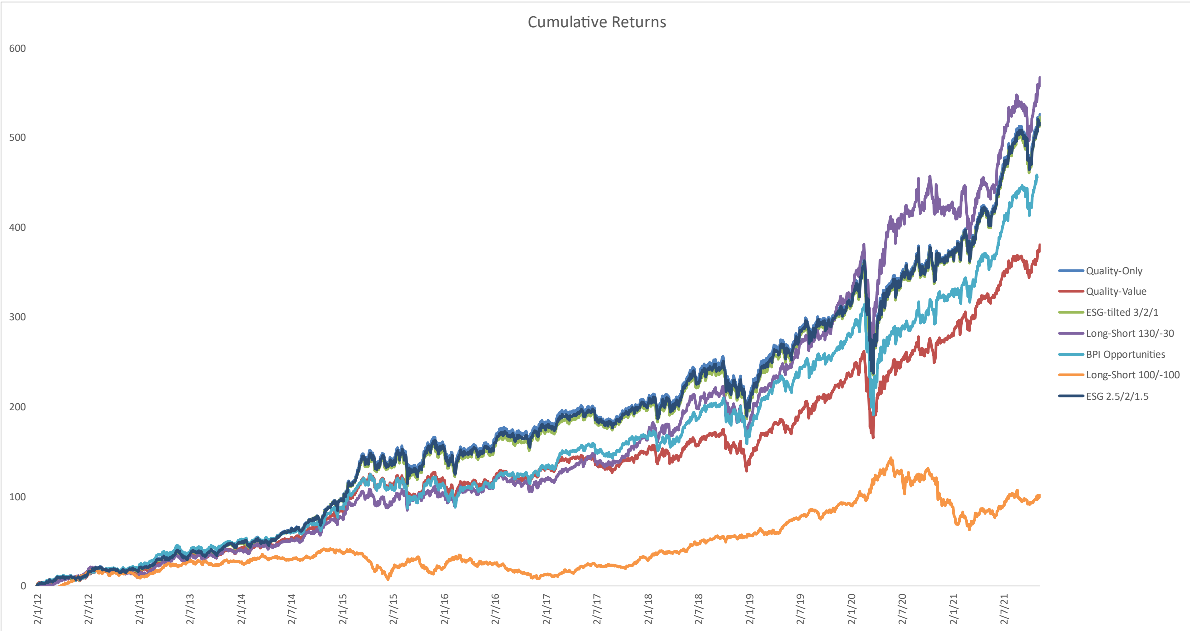
Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Regressions of excess returns of the strategies created on systematic risk factors using the Bloomberg 5-Factor Model, over the period from December 2011 until September 2021.

XVIII. Cumulative returns of the new strategies

Sample period: 2011/12/31 – 2021/09/30

Annex 34: Cumulative returns of new strategies

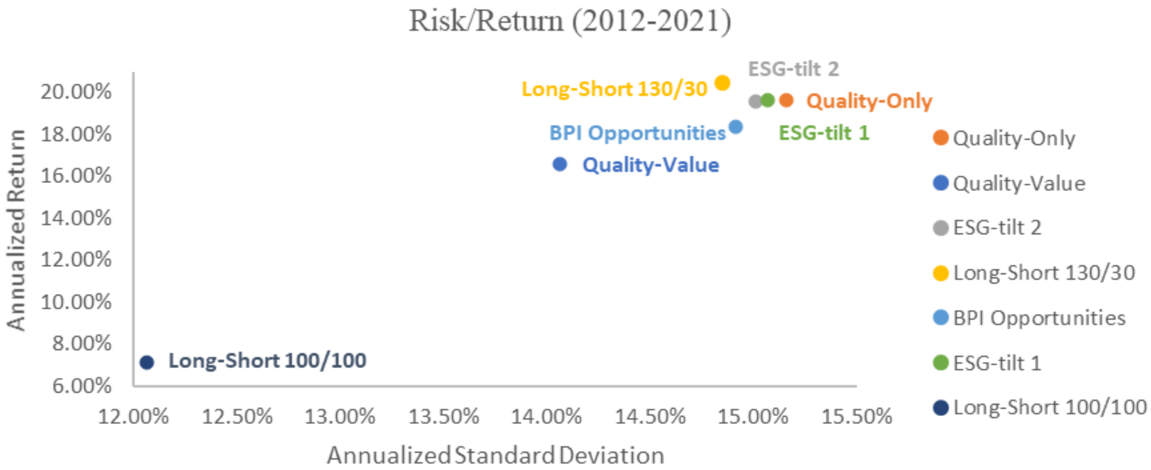


Cumulative returns of all new strategies and BPI Opportunities from December 2011 until September 2021.

XIX. Risk/ Return characteristics of the new strategies

Sample period: 2011/12/31 – 2021/09/30

Annex 35: Risk-Return profile of the new strategies (2012-2021)



Plot of risk-return profile (annualized return vs. annualized standard deviation) of all newly created strategies and BPI Opportunities.

XX. Bloomberg regressions in dollars

Annex 36 – Bloomberg Regression (True Sample Period, USD)

	BL Factors (True sample period, USD)	
	CAPM	5-Factor Model
const	0.001**	0.001**
	(0.001)	(0.000)
MKT-RF	0.897***	1.025***
	(0.022)	(0.023)
Momentum		0.413***
		(0.078)
Size		0.111
		(0.193)
Value		-0.606***
		(0.198)
Profit		0.959***
		(0.142)
Observations	140	140
R^2	0.925	0.964
Adjusted R^2	0.924	0.963
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01

Annex 36 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the Bloomberg 5-Factor Model, over the true sample period (USD).

Annex 37 – Bloomberg Regressions (Joint Sample, USD)

	BL Factors (Joint Sample Period, USD)	
	CAPM	5-Factor Model
const	0.001***	0.001***
	(0.000)	(0.000)
MKT-RF	0.845***	0.935***
	(0.010)	(0.017)
Momentum		0.305***
		(0.056)
Size		-0.239**
		(0.114)
Value		-0.274**
		(0.113)
Profit		0.987***
		(0.124)
Observations	932	932
R^2	0.894	0.912
Adjusted R^2	0.894	0.911
Standard errors in parentheses		*p<0.1; **p<0.05; ***p<0.01

Annex 37 depicts the output of the regressions of BPI Opportunities excess returns on systematic risk factors using the CAPM and the Bloomberg 5-Factor Model, over the joint sample period (USD).

14. References

Ang, A. and Framsted, H. n.d. 'Multifactor Strategies'. https://www.blackrock.com/institutions/en-axj/insights/factor-perspectives/multi-factor-strategies.

Asness, Clifford, Andrea Frazzini, Ronen Israel, Tobias J. Moskowitz, and Lasse H. Pedersen. 2018. 'Size Matters, If You Control Your Junk'. *Journal of Financial Economics* 129 (3): 479–509. https://doi.org/10.1016/j.jfineco.2018.05.006.

Asness, Clifford, Andrea Frazzini, and Lasse Pedersen. 2019. 'Quality Minus Junk'. *Review of Accounting Studies* 24 (March). https://doi.org/10.1007/s11142-018-9470-2.

Asness, Clifford S., Andrea Frazzini, and Lasse Heje Pedersen. 2017. 'Quality Minus Junk'. SSRN Scholarly Paper ID 2312432. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.2312432.

Baca, Sean P., Brian L. Garbe, and Richard A. Weiss. 2000a. 'The Rise of Sector Effects in Major Equity Markets'. *Financial Analysts Journal* 56 (5): 34–40. https://doi.org/10.2469/faj.v56.n5.2388.

———. 2000b. 'The Rise of Sector Effects in Major Equity Markets'. *Financial Analysts Journal* 56 (5): 34–40. https://doi.org/10.2469/faj.v56.n5.2388.

Banz, Rolf W. 1981. 'The Relationship between Return and Market Value of Common Stocks'. *Journal of Financial Economics* 9 (1): 3–18. https://doi.org/10.1016/0304-405X(81)90018-0.

Basu, S. 1977. 'Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis'. *The Journal of Finance* 32 (3): 663–82. https://doi.org/10.1111/j.1540-6261.1977.tb01979.x.

Beck, Noah, Jason Hsu, Vitali Kalesnik, and Helge Kostka. 2016. 'Will Your Factor Deliver? An Examination of Factor Robustness and Implementation Costs'. CFA Institute. 2016. https://www.cfainstitute.org/en/research/financial-analysts-journal/2016/will-your-factor-deliver-an-examination-of-factor-robustness-and-implementation-costs.

Bender, J. and Briand, J. 2013. 'Foundations of Factor Investing'. MSCI Index Research. https://www.msci.com/documents/1296102/1336482/Foundations_of_Factor_Investing.pdf.

Black, Fischer. 1972. 'Capital Market Equilibrium with Restricted Borrowing'. *The Journal of Business* 45 (3): 444–55.

Bodie, Zvi, Alan Marcus, and Alex Kane. 2014. *Investments*. McGraw-Hill Education. http://www.mim.ac.mw/books/Bodie's%20Investments,%2010th%20Edition.pdf.

Bouchaud, Jean-Philippe, Ciliberti Stefano, Augustin Landier, Guillaume Simon, and David Thesmar. 2016. ‘The Excess Returns of “Quality” Stocks: A Behavioral Anomaly’. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2717447.

BPI Gestão de Ativos. 2020. ‘BPI Gestão de Ativos - Relatório e Contas’. BPI Gestão de Ativos. https://www.bancobpi.pt/contentservice/getContent?documentName=PR_WCS01_UCM01010653.

Breedt, Andre, Stefano Ciliberti, Stanislao Gualdi, and Philip Seager. 2018. ‘Is ESG an Equity Factor or Just an Investment Guide?’, 11.

Bruno, G., Esakia, M., and Goltz, F. 2021. ‘“Honey, I Shrunk the ESG Alpha”: Risk-Adjusting ESG Portfolio Returns’. ScientificBeta. https://cdn.ihsmarkit.com/www/pdf/0521/Honey-I-Shrunk-the-ESG-Alpha.pdf.

Buffett, Warren E. 1989. ‘Letter to Shareholders’, 1989. https://www.berkshirehathaway.com/letters/1989.html.

Carhart, Mark M. 1997. ‘On Persistence in Mutual Fund Performance’. *The Journal of Finance* 52 (1): 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x.

Chen, Jianguo, Andrea Bennett, and Ting Zheng. 2006. ‘Sector Effects in Developed vs. Emerging Markets’. *Financial Analysts Journal* 62 (6): 40–51. https://doi.org/10.2469/faj.v62.n6.4352.

‘Clarke, Silva, & Thorley 2016 - Fundamentals of Efficient Factor Investing - November/December 2016’. n.d. StuDocu. Accessed 11 November 2021. https://www.studocu.com/pt-br/document/fundacao-universidade-federal-do-rio-grande/vestibular/clarke-silva-thorley-2016-fundamentals-of-efficient-factor-investing/1384919.

Dichev, Ilia D. 1998. ‘Is the Risk of Bankruptcy a Systematic Risk?’ *The Journal of Finance* 53 (3): 1131–47. https://doi.org/10.1111/0022-1082.00046.

Fama, Eugene F., and Kenneth R. French. 1992. ‘The Cross-Section of Expected Stock Returns’. *The Journal of Finance* 47 (2): 427–65. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x.

FAMA, EUGENE F., and KENNETH R. FRENCH. 1992. ‘The Cross-Section of Expected Stock Returns’. *The Journal of Finance* 47 (2): 427–65. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x.

Fama, Eugene F., and Kenneth R. French. 1993. ‘Common Risk Factors in the Returns on Stocks and Bonds’. *Journal of Financial Economics* 33 (1): 3–56. https://doi.org/10.1016/0304-405X(93)90023-5.

———. 2015. ‘A Five-Factor Asset Pricing Model’. *Journal of Financial Economics* 116 (1): 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010.

Frazzini, Andrea, and Lasse Heje Pedersen. 2014. ‘Betting against Beta’. *Journal of Financial Economics* 111 (1): 1–25. https://doi.org/10.1016/j.jfineco.2013.10.005.

Fruhan, William E. 1979. *Financial Strategy: Studies in the Creation, Transfer, and Destruction of Shareholder Value*. Homewood, Ill: R. D. Irwin.

FTSE, Russell. 2014. ‘Factor Exposures Indexes - Value Factor’, 2014. https://www.ftserussell.com/research/factor-exposure-indexes-value-factor.

FTSE Russell. 2018. ‘Top-down or Bottom-Up?’ FTSE Russell. https://content.ftserussell.com/sites/default/files/research/top_down_or_bottom_up.pdf.

Giese, Guido, Linda-Eling Lee, Dimitris Melas, Zoltán Nagy, and Laura Nishikawa. 2019. ‘Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance’. *The Journal of Portfolio Management* 45 (5): 69–83. https://doi.org/10.3905/jpm.2019.45.5.069.

Glück, Maximilian, Benjamin Hübel, and Hendrik Scholz. 2020a. ‘Currency Conversion of Fama/French Factors: How and Why’. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3437648.

———. 2020b. ‘Currency Conversion of Fama–French Factors: How and Why’. *The Journal of Portfolio Management*, November, jpm.2020.1.192. https://doi.org/10.3905/jpm.2020.1.192.

González-Urteaga, Ana, and Gonzalo Rubio. 2021a. ‘The Quality Premium with Leverage and Liquidity Constraints’. *International Review of Financial Analysis* 75 (C). https://ideas.repec.org/a/eee/finana/v75y2021ics1057521921000429.html.

———. 2021b. ‘The Quality Premium with Leverage and Liquidity Constraints’. *International Review of Financial Analysis* 75 (February): 101699. https://doi.org/10.1016/j.irfa.2021.101699.

Graham, Benjamin, 1894-1976. 1959. *The Intelligent Investor: A Book of Practical Counsel*. [Second revised edition]. New York : Harper, [1959]. https://search.library.wisc.edu/catalog/999688336402121.

Griffin, D., A. Tversky, and Stanford Center on Conflict and Negotiation. 1993. *The Weighing of Evidence and the Determinants of Confidence*. Stanford Center on Conflict and Negotiation, Stanford University. https://books.google.pt/books?id=dGIrAQAAIAAJ.

Gupta, Abhishek, Altaf Kassam, Raghu Suryanarayanan, and Katalin Varga. 2014. ‘Index Performance in Changing Economic Environments’, 43.

Hanauer, Matthias Xaver, and Technische Universität München. 2014. 'Risk Factors and Capital Market Anomalies', 193.

Henriksson, Roy, Joshua Livnat, Patrick Pfeifer, and Margaret Stumpp. 2019. 'Integrating ESG in Portfolio Construction'. *The Journal of Portfolio Management* 45 (4): 67–81. https://doi.org/10.3905/jpm.2019.45.4.067.

Hsu, Jason, Vitali Kalesnik, and Engin Kose. 2019. 'What Is Quality?' *Financial Analysts Journal* 75 (2): 44–61. https://doi.org/10.1080/0015198X.2019.1567194.

Hull, John, 1946-. 2012. *Options, Futures, and Other Derivatives*. Eighth edition. Boston : Prentice Hall, [2012] ©2012. https://search.library.wisc.edu/catalog/9910112878402121.

Hunstad, Michael. 2020. 'Commentary: As Factor-Based Investing Grows, Beware the Combo Platter'. Pensions & Investments. 12 March 2020. https://www.pionline.com/industry-voices/commentary-factor-based-investing-grows-beware-combo-platter.

James Kinghorn. 2018. 'INVESTING FOR THE LONG TERM: "FUTURE QUALITY" COMPANIES', 5.

Jensen Investment Management. 2021. 'High Quality Stocks and Inflation Resilience'. Jensen Investment Management. https://www.jenseninvestment.com/wp-content/uploads/2021/06/high-quality-stocks-inflation-resilience-%E2%80%93-jensen-insights-june-2021.pdf.

Jordan Dekhayser. 2018. 'Is ESG a Factor'. Northern Trust Asset Management. https://www.northerntrust.com/documents/pov-reprint/is-esg-a-factor.pdf.

Khan, Mozaffar, George Serafeim, and Aaron Yoon. 2016. 'Corporate Sustainability: First Evidence on Materiality by Mozaffar Khan, George Serafeim, Aaron Yoon :: SSRN'. 2016. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2575912.

Kulkarni, Padmakar, Abhishek Gupta, and Stuart Doole. 2018a. 'How Can Factors Be Combined?', 27.

Kulkarni, Padmakar, Abhishek Gupta, and Suart Doole. 2018b. 'How Can Factors Be Combined?' MSCI. https://www.msci.com/documents/10199/ff891dc6-61ac-9d77-1f39-aeb0113a767d.

Lempérière, Y., C. Deremble, T. T. Nguyen, P. Seager, M. Potters, and J. P. Bouchaud. 2017. 'Risk Premia: Asymmetric Tail Risks and Excess Returns'. *Quantitative Finance* 17 (1): 1–14. https://doi.org/10.1080/14697688.2016.1183035.

Lepetit, Frederic, Amina Cherief, Yannick Ly, and Takaya Sekine. 2021a. 'Revisiting Quality Investing'. *SSRN Electronic Journal*, June. https://doi.org/10.2139/ssrn.3877161.

———. 2021b. ‘Revisiting Quality Investing’. *SSRN Electronic Journal*, June. https://doi.org/10.2139/ssrn.3877161.

Lintner, John. 1965. ‘SECURITY PRICES, RISK, AND MAXIMAL GAINS FROM DIVERSIFICATION*’. *The Journal of Finance* 20 (4): 587–615. https://doi.org/10.1111/j.1540-6261.1965.tb02930.x.

Liu, Weimin. 2006. ‘A Liquidity-Augmented Capital Asset Pricing Model’. *Journal of Financial Economics* 82 (3): 631–71. https://doi.org/10.1016/j.jfineco.2005.10.001.

Markowitz, Harry. 1952. ‘Portfolio Selection’. *The Journal of Finance* 7 (1): 77–91. https://doi.org/10.2307/2975974.

Melas, Dimitris, Zoltan Nagy, and Padmakar Kulkarni. 2016. ‘Factor Investing and ESG Integration’. In *Factor Investing*, 389–413. Elsevier. https://doi.org/10.1016/B978-1-78548-201-4.50015-5.

Michael Hunstad. 2013. ‘Insights on - Defining Quality’. Northern Trust Asset Management. https://supplements.pionline.com/uploads/supplements/Insights_On_-_Defining_Quality.pdf.

Morgan Stanley Institute for Sustainable Investing. 2019. ‘Sustainable Reality: Analyzing Risk and Returns of Sustainable Funds’. https://www.morganstanley.com/content/dam/msdotcom/ideas/sustainable-investing-offers-financial-performance-lowered-risk/Sustainable_Reality_Analyzing_Risk_and_Returns_of_Sustainable_Funds.pdf.

Nagy, Zoltán, Zoltan Nagy, Doug Cogan, Doug Cogan, Dan Sinnreich, and Dan Sinnreich. 2013. ‘Optimizing Environmental, Social, and Governance Factors in Portfolio Construction’, 17.

Norges Bank. 2015. ‘The Quality Factor’, December 2015. https://www.nbim.no/contentassets/0660d8c611f94980ab0d33930cb2534e/nbim_discussionnotes_3-15.pdf.

Northern Trust Asset Management. 2014. ‘Combining Risk Factors For Superior Returns’. https://www.northerntrust.com/documents/white-papers/asset-management/combining-factors-equity.pdf?bc=24164092.

Novy-Marx, Robert. 2012. ‘Quality Investing’. In .

———. 2013. ‘The Other Side of Value: The Gross Profitability Premium’. *Journal of Financial Economics* 108 (1): 1–28. https://doi.org/10.1016/j.jfineco.2013.01.003.

———. n.d. ‘The Other Side of Value: The Gross Profitability Premium’, 73.

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski. 2020. 'Responsible Investing: The ESG-Efficient Frontier | Elsevier Enhanced Reader'. 2020. https://doi.org/10.1016/j.jfineco.2020.11.001.

Polychronopoulos, Ari, and John West. 2020. 'Is ESG a Factor? | Research Affiliates'. Researchaffiliates.Com. 2020. https://www.researchaffiliates.com/publications/articles/813-is-esg-a-factor.html.

Reddy, Rohan. 2019. 'Quality Dividend Stocks in Volatile Markets'. Global X ETFs. 5 March 2019. https://www.globalxetfs.com/quality-dividend-stocks-in-volatile-markets/.

Ross, Stephen A. 1976. 'The Arbitrage Theory of Capital Asset Pricing'. *Journal of Economic Theory* 13 (3): 341–60. https://doi.org/10.1016/0022-0531(76)90046-6.

Sedeek, Doaa Samy, and Khairy Elgiziry. 2020. 'DOES QUALITY STOCK OUTPERFORM THE MARKET IN DOWNTURN PERIODS?' *International Journal of Business, Accounting and Finance* 14 (1): 1+.

Sharpe, William F. 1964. 'CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK*'. *The Journal of Finance* 19 (3): 425–42. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x.

S&P Dow Jones Indices. 2019. 'Combining The Quality Factor with Dividend Yield: A Study of S&P DJI Dividend Strategies'. Combining The Quality Factor with Dividend Yield: A Study of S&P DJI Dividend Strategies. July 2019. https://seekingalpha.com/article/4233926-combining-quality-factor-dividend-yield-study-of-s-and-p-dji-dividend-strategies.

Steinbarth, Emily, and Scott Bennett. 2018. 'Materiality Matters: Targeting the ESG Issues That Impact Performance'. *The Harvard Law School Forum on Corporate Governance* (blog). 10 May 2018. https://corpgov.law.harvard.edu/2018/05/10/materiality-matters-targeting-the-esg-issues-that-impact-performance/.

———. n.d. 'Materiality Matters: Targeting the ESG Issues That Can Impact Performance - the Material ESG Score', 30.

Ung, Daniel, Priscilla Luk, and Xiaowei Kang. 2014a. 'Quality: A Distinct Equity Factor?', 22.

———. 2014b. 'Quality: A Distinct Equity Factor?' SSRN Scholarly Paper ID 2472391. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.2472391.

Zhang, X. 2006. 'Information Uncertainty and Stock Returns'. *Journal of Finance* 61 (February): 105–37. https://doi.org/10.2139/ssrn.535783.

A Work Project, presented as a part of the requirements for the Award of a Master's Degree in Finance from Nova School of Business and Economics

Decoding the Quality Factor:

Quality Investing in Emerging Markets

Lorenz Ambrosius

Work project carried out under the supervision of:

Professor Giorgio Ottonello

17-12-2021

Abstract

This master thesis forms part of a series of papers seeking to provide academic guidance on practical issues encountered by BPI Gestão de Ativos (BPI GA) and test the effectiveness of quality investing strategies in emerging markets. By applying BPI GA’s quality strategy and equity screen to a predominantly Brazilian investment universe and running regression analysis using Fama French emerging market factors, it was confirmed that (1) BPI GA's quality investing strategy creates value in emerging markets, (2) the quality premium exists in Brazil, (3) the Brazilian market has a relatively low number of quality companies, (4) BPI GA's quality strategy is sensitive to the size of the investment universe it is applied to and (5) quality equity screens perform poorly in emerging markets. Thus, the final recommendation was to apply BPI GA’s quality investing strategy to a large investment universe spanning multiple emerging markets.

Keywords: Factor Investing; Quality Investing; Emerging Markets Equity; Brazilian Equity Market; Asset Management

Acknowledgments

I would like to express my sincere gratitude to my business advisors, Professor Jorge Sousa Teixeira, Luís Alvarenga, Rui Araújo, and Sofia Jesus, for their support, insightful feedback, and engaging discussions throughout the project. Furthermore, I would like to extend my gratitude to my supervisor Professor Giorgio Ottonello for his valuable recommendations, feedback, and guidance.

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Table of Contents

Table of Figures

Table of Appendix

1. Introduction

The emerging markets equity share of the global equity market may overtake that of the developed world by 2030. While the share of the emerging market assets continues to increase, few researchers have analyzed the performance of quantitative investment strategies in emerging markets. At present, emerging markets hold 26% of the global market cap, up from 4% in 2003 (Wagstyl 2010) (Lee 2010). Equally, the emerging markets' global GDP share increased from 20% in 1980 to 39% in 2020 (Morgan Stanley 2021). In line with this development, international investors are increasingly seeking to increase their exposure to these markets. Research suggests that style investing strategies may be successful strategies, but little is known about the efficiency of quality investment strategies in the space.

This master thesis aims to shed light on the efficiency of quality investing strategies in emerging markets, relying on evidence from Brazil. The paper sets out to confirm the hypothesis that quality investing, following BPI GA's approach, creates value in emerging markets. It applies a quality investing strategy developed by BPI GA to a majority Brazilian investment universe to provide evidence (1) on the effectiveness of BPI GA's quality investing strategy in emerging markets, (2) existence of the quality premium in Brazil, (3) and the number of quality companies in Brazil compared to the developed world, (4) test the sensitivity of BPI GA's quality strategy on the size of the investment universe, (5) and the effectiveness of quality equity screens in emerging markets.

Firstly, the paper will introduce relevant theoretical concepts and literature. Secondly, it will go over the data used for the analysis and confirm the validity of the Fama French factor model through a robustness test. Thirdly, the performance statistics and factor exposure of two quality strategies and the Brazilian market will be presented. Fourthly, the results will be discussed, performance statistics of the market and two strategies compared and limitations and areas for future research pointed out. Finally, a conclusion will be presented.

2. *Literature Review*

Research suggests that active management may be most effectively deployed in emerging markets. AQR's (2010) research suggests that active management stands to benefit the most from market inefficiencies. Financial market regulations, government interventions, and the number of active managers impact the success of the active approach. Restriction or interference of short selling (as observed in Brazil)[1] can prevent inflated equity valuations from correcting. Government interventions such as tariffs or import restrictions can result in more exploitable inefficiencies. Finally, fewer sophisticated, active managers try to profit from inefficiencies in emerging equity markets. Hence, AQR (2010) finds that emerging market equities provide excellent opportunities for active managers to generate excess returns (Lee 2010).

Nevertheless, Mackenzie (2021), Foy (2018), and Leite et al. (2018) find evidence that factor investing can be effective in emerging markets. Running a simple factor analysis on portfolios that blend stocks with value and momentum characteristics, Mackenzie (2021) finds significantly larger alpha in emerging markets -particularly in small caps- than in the US or other developed markets (Mackenzie Investments 2021). Moreover, Foy (2018) and Leite et al. (2018) find evidence that factor analysis of emerging equity markets using factors constructed following Fama French's approach do a good job explaining the market. Foy (2018) finds that there is a pronounced value premium across emerging markets as well as a significant profitability premium (RMW) in Latin American and Eastern Europe, while the size and investment factors are insignificant across the emerging markets (Foye 2018). Conversely, Leite et al. (2018) show an apparent size effect on stock excess market returns across emerging

[1] Through tax exemptions that encourage individual investors to lent equity to mutual funds on before dividend record day (Barbosa, et al. 2019)

markets, while profitability and value have no evident effect on excess returns (Leite et al. 2018).

This thesis will fill the research gap by applying quality investing strategies to a majority Brazilian stock universe. While past research provides evidence that active management and factor investing can succeed in emerging markets if done correctly, little research on the existence of a quality premium in emerging markets has been published in internationally renowned journals. Moreover, there is a lack of research on applying factor investing strategies to a stock universe focused on a single emerging markets country and on applying quality investing approaches in emerging markets. This master thesis will fill the existing gap by applying a quality investing strategy and a quality equity screen to a majority Brazilian stock universe, thereby proving the existence of a quality premium in Brazil, providing evidence that quality investing in emerging markets can create value, testing the effectiveness of quality equity screens in emerging markets, and answering whether there are enough quality companies in a small emerging market stock universe to apply quality investing strategies successfully.

3. Theoretical Foundations

3.1 Factor Investing

Factor models explain security returns through their exposure to certain risk factors. Factor investing systematically targets factor premiums identified through research. It is an investment strategy targeting specific drivers of a return across different investment universes and asset classes (BlackRock 2018).[2]

3.2 Defining Quality

Quality can be defined as a combination of a company's profitability and investing activity attributes. Most practitioners and academics define quality companies as those with

[2] For more information refer to the collective group work

heightened profitability, stable income and cash flows, and a lack of excessive leverage (Nielson, Nielsen und Barnes 2016). These characteristics are in line with findings from Novy-Marx (2013), Fama and French (2015), Hsu et al. (2019) and others, finding positive premiums associated with profitability characteristics of companies (Hsu, Kalesnik und Kose 2019), (Novy-Marx 2013).[3]

4. Data and Methodology

4.1 Data

4.1.1 Input Data

Data used to run the analysis was extracted from Bloomberg and FactSet. The indices retrieved for the robustness check and analysis of the Brazilian equity market were extracted from Bloomberg and denominated in US dollar and Brazilian Real. The indices used include: Fidelity Emerging Markets Quality Income Index (ticker: FIDEMQIN), MSCI Emerging Markets Value Weighted Index (M1EF000V), MSCI Emerging Markets Small-Cap ETF (EEMS), and iShares Ibovespa Fundo de Indice (BOVA11), a fund that aims to reproduce the performance of the Ibovespa Index. The time period used for analysis starts in January 2010 and ends in November 2021, except for the small-cap index, which was only incepted in August 2011. The data used for the quality strategy has been extracted from FactSet; only the WACC has been retrieved from Bloomberg. The data is consistent across the analyzed period from January 2012 to November 2021. Given the small stock sample in existing Brazilian indices, it was decided to create a custom universe that also includes publicly traded companies that generated more than 10% of their revenue in Brazil on the 25th of November 2021. The static stock universe was chosen due to download restrictions using FactSet. Finally, the equity screen relies exclusively on data from Bloomberg.

[3] For more information refer to the collective group work

4.1.2 Factors

The factor analysis relies on Fama French emerging market factors. To determine whether the factors are reliable, a robustness test was conducted. The factors have been retrieved from the Kenneth R. French Data Library. CMA and RMW constitute the quality factors, with RMW being the main quality factor.[4]

4.2 Model

4.2.1 Quality Filter

A python model relying on input data from BPI GA's quality excel model has been developed to sort for the companies with the highest quality. The model runs several exclusions in line with BPI GA's exclusions criteria. Subsequently, it creates multiple independent rankings evaluating different dimensions of quality. Most notably, the model computes a firm's value creation "value" and ranks them afterward to identify those firms creating the most value. The “value" is a simplified discounted cash flow analysis, relying on the average growth of the firm, the average return on invested capital, and the weighted average costs of capital. Moreover, all firms are independently ranked on the following criteria: average ROCE over the past three years, average EBIT margin over the past three years, the average ROCE stability over the past four years, the average EBIT margin stability over the past four years, and the gross margin stability over the past four years. Subsequently, an absolute quality score is derived by applying the following formula to the rank values of all companies in the stock universe:

(1) $Quality\ Score = 6 \times Value\ Creation\ Rank + 1 \times Avg. ROCE\ L3Y +$

$2 \times Avg. EBIT\ Margin\ L3Y\ Rank + 1 \times ROCE\ 4Y\ Stability\ Rank +$

$1 \times EBIT\ Margin\ 4Y\ Stability\ Rank + 1 \times L4Y\ GR\ Stability\ Rank$

[4] For further information refer to the Kenneth R. French Data Library and the collective group thesis

Finally, the quality score is ranked, and the top 25 holdings are added to the portfolio. The quality model rebalances quarterly, filtering for the top-quality holdings once a quarter. The holdings of each quarter are uploaded to Bloomberg PORT, and the program computes the strategy's returns.

Nevertheless, the strategy was adjusted for this master thesis. The exclusion criteria used in the quality filter were taken out as applying the criteria decreased the investment universe excessively. Applying the exclusion criteria to the stock universe reduced the number of companies from 593 to 21 in the most recent quarter. Thus, it was decided to omit the exclusions from the model and focus on identifying quality companies in a universe that does not exclude non-quality companies.

4.2.2 Equity Screen

Bloomberg's equity screen function is used to identify the changing number of companies that comply with a fixed set of quality criteria. This equity screen is performed to determine whether there are sufficient quality companies at any given point in time during the analyzed period. The following criteria and thresholds were used to identify quality companies: market capitalization (>$300 Mio.), Altman Z-score (>=2.7), operating margin (>=10%), ROIC (>=15%), and gross profitability (>=0.25). The gross profitability indicator is gross profitability trailing 12 months divided by total assets. Its use is in line with Novy-Marx's (2013) findings that gross profitability as a quality indicator has as much power in predicting stock returns as traditional value indicators. After identifying quality companies under the above criteria, a backtest was run to determine the strategy's performance between February 2012 and November 2021. The filter was applied to all publicly traded companies that Bloomberg categorized as Brazil domiciled.

4.3 Data Manipulation

Consistency of the data was ensured by converting certain data into monthly frequency. The Fama French style factors are provided with a monthly frequency. The returns of the strategies tested have been converted into monthly returns to ensure comparability with the factor model. Resampling of daily or weekly returns was achieved by converting arithmetic returns to logarithmic ones and summing them to monthly returns. Advantage of these conversions comes from normally distributed returns, which are considered superior as most statistical analyses assume normality.

In the context of regression analysis, tests for heteroskedasticity were run, and adjustments to the standard errors were made where necessary. The Breusch-Pagan test was used to test for the existence of heteroskedasticity. Newey–West standard errors with a time lag of one were integrated in the presence of heteroskedasticity. The use of the Newey-West variance estimators produces consistent estimates in the presence of autocorrelation and heteroskedasticity. Hence, Newey–West standard errors ensure the robustness of the model and precision of estimates (Petersen 2009).

The factor analysis was run using the Fama French emerging market factors. The Fama Frenchs factors HML (value), SMB (size), CMA (conservative investing), RMW (profitability), and market premium are relied upon as explanatory variables, and the excess returns of the respective strategy or market are used as the dependent variables. The regression formula is given by:

(2) $R_{QS,ES,M} - r_f = \alpha + \beta_1(MKT - RF)$

(3) $R_{QS,ES,M} - r_f = \alpha + \beta_1(MKT - RF) + \beta_2(SMB) + \beta_3(CMA) + \beta_4(HML) + \beta_5(RMW)$

Where QS is the quality strategy, ES the quality equity screen, and M the market.

5. Robustness Tests

The robustness test aims to confirm the validity and explanatory power of the Fama French factor model. The following emerging market style indices are used to confirm the validity of the factors through means of regression: Fidelity Emerging Markets Quality Income Index (ticker: FIDEMQIN), MSCI Emerging Markets Value Weighted Index (M1EF000V), MSCI Emerging Markets Small-Cap ETF (EEMS). The analyzed period starts in August 2011 and ends in November 2021. The index returns used for the robustness tests are denominated in USD. Regression results confirming the validity of the models should exhibit high adjusted R-squared, low or insignificant alphas, and positive and statistically significant style coefficients that correspond with the respective style of the index.

5.1 Robustness Results

The robustness test results suggest the model's validity. Significant and positive coefficients robust minus weak and conservative minus aggressive can be observed when regressing the emerging markets quality index onto the model. Equally, one can observe a high, statistically significant small minus big coefficient when regressing the emerging market small-cap index onto the factors. In line with this, the value index exhibits a positive and statistically significant coefficient high minus low when regressed onto the Fama French model. Furthermore, a high adjusted R-squared of 0.98, 0.93, and 0.99 can be observed (Appendix 1). Finally, all regression results exhibit a very low alpha. These results are even more explicit when extending the regression period for the quality and value indices to January 2010. Hence, it can be concluded that the Fama French factors explain returns in emerging markets well. However, it should be pointed out that the strategies tested focus on the Brazilian market. Thus, the conclusion drawn from this test may prove to be less valid for an analysis focusing solely on Brazilian equity.

6. The Brazilian Equity Market

6.1 Characteristics

The Brazilian equity market differs from more sophisticated equity markets in its high ownership concentration, different financing practices, and a strong focus on large-cap companies as well as specific economic sectors. The high ownership concentration is a critical difference between the Brazilian and developed world equity markets. In 2017, 79% of publicly traded companies had majority or shared control shareowners. Equally, Brazilian firms' primary funding source are retained earnings, while funding from capital markets and bank credits is less common. Moreover, there are very few small and medium-sized companies listed. Finally, the equity market exhibits a strong sector focus on consumer goods (35%), finance (17%), industrial goods (16%), and public utilities (13%) (OECD 2019).

6.2 Currency

The volatility of the Brazilian Real adversely impacts its equity market as it deters foreign investors. The US dollar to Brazilian Real exchange rate has dramatically changed over the past 11 years. While the USD/Real exchange rate in February 2010 stood at 1.89, the exchange rate in October 2021 marked an all-time high of 5.64 (Appendix 2, Appendix 3). This decrease in value poses a significant threat to foreign investors as they risk losing money due to foreign exchange effects even when the Brazilian equity market is expanding.

7. Results

7.1 Brazilian Market

7.1.1 Historic Returns

The Brazilian equity market has performed poorly over the past eleven years, a circumstance that is further aggravated if returns are analyzed in USD. While BOVA11 generates low but positive annual returns of 5.62% in Real, its US dollar returns are -5.72%

annually. Equally, there is a significant market volatility, with a standard deviation of 25.54% in Real and 34.66% in USD terms. Consequently, a risk-reward ratio of 0.22 in Real and a risk-reward ratio of -0.17 in USD are observed (Appendix 4, Appendix 5)[5].

7.1.2 Factor Exposure

BOVA11 exhibits a statistically significant exposure to the market with a coefficient of 1.36. Similarly, the Brazilian index exhibits a high exposure to value and returns associated with conservative investing. Conversely, the index returns are negatively correlated to the profitability factor RMW. Moreover, an extremely low and negative alpha can be observed. All coefficients are statistically significant at the 95th confidence interval, except for the market that is statistically significant at the 99th confidence interval. Finally, it can be concluded that Fama French factors do a good job explaining the return of the Brazilian equity market, with an adjusted R-squared equal to 0.72 (Appendix 6).

7.2 Quality Strategy

7.2.1 Country Exposure

Applying the quality filter to the investment universe resulted in significant geographic exposure to Brazil and other South American countries. Across the backtested period, an exposure of 70% to the Brazilian market, 7% to the Mexican market, 5.5% to the Chilean market, and residual exposure to the Argentinian, Peruvian, and other countries was observed. However, there was also some exposure to the developed world with an average exposure of 10% to the US and 3% to the UK.

7.2.2 Performance

The analyzed strategy has outperformed the market (BOVA11) in USD and Real terms between January 2012 and September 2021. Comparing the quality strategy to the market in USD, a significant increase in returns from -5.72% to 4.01% and a reduction in volatility from

[5] Negative risk reward ratios yield no explanatory power

34.7% to 22.9% can be observed. Thus, the risk-reward ratio improves from -0.17 to 0.18. Similarly, the quality strategy outperforms the market in Real returns. Applying the strategy to the stock universe defined in the input data section, leads to an increased average annual return from 5.62% to 15.77% and a reduction in volatility from 25.5% to 15.3%. Hence, the risk-reward ratio increases from 0.22 to 1.03 when comparing the performance of the Brazilian equity market with the quality strategy (Appendix 4, Appendix 7).

7.2.3 Factor Exposure

The quality strategy exhibits considerable exposure to the market and the factor CMA. The strategy has a market beta of 1.19 and a large conservative minus aggressive investing coefficient of 1.06. The coefficients are statistically significant at the 99th confidence interval and the adjusted R-squared is equal to 0.64 (Appendix 8).

7.3 Equity Screen

7.3.1 Existence of Quality Companies

Applying the equity screen to all publicly traded Brazil-domiciled companies produces mixed results, but reveals the existence of some quality companies. The equity screen was applied annually to an average of 243 publicly traded Brazilian companies between 2012 and 2021 to determine whether there are sufficient quality companies in Brazil. Using the equity screen, an average of 13 companies have been identified that comply with the minimum quality criteria. However, the number fluctuated significantly, with as few as five companies passing the screen in 2020, while 23 companies complied with the criteria in December 2021. Hence, an average of 5.5% of the publicly traded Brazilian companies have passed the equity screen across the analyzed period (Appendix 9). For comparability, the screen was also applied to the MSCI World. Computing the ratio of companies that passed the screen- analyzing the period from 2015 to 2021- yielded an average ratio of 8.9% or 159 companies (Appendix 10).

7.3.2 *Performance*

The equity screen underperformed the market both in USD and Real terms. The Brazilian equity market exhibits a risk-reward ratio of 0.22 between March 2012 and September 2021, while the equity screen exhibits a risk-reward ratio of 0.19 in Real. Equally, the average annual losses in USD are higher for the equity screen (-7.41%) than for the Brazilian market (-5.72%). However, applying the equity screen reduced volatility marginally compared to the overall market (Appendix 4).

7.3.3 *Factor Exposure*

There is little evidence that the equity screen increases exposure to the quality factors. Regressing the equity screen returns onto the Fama French factors, a high value coefficient of 1.14 (at the 90^{th} confidence interval) and substantial exposure to the market (1.44 at the 99^{th} confidence interval) can be observed (Appendix 11).

8. *Discussion*

8.1 *Analysis of the Market*

The Brazilian equity market exhibits positive exposure to the factors associated with conservative investing firms, value, and the market as well as negative exposure to the profitability factor RMW. Hence, the Brazilian market returns are driven by "the market" – as defined by Fama French’s emerging market factor model- and returns associated with conservative investing, while returns associated with profitability negatively affect the market's returns. Thus, evidence from the Brazilian market contradicts Foy's (2018) findings, suggesting the existence of a pronounced profitability premium- robust minus weak- in Latin America (Appendix 6).

8.2 *Analysis of the Quality Strategy*

8.2.1 *Performance Analysis*

Applying the quality strategy to a majority Brazilian stock universe produces returns that are superior to the benchmark. This improvement in risk-adjusted returns indicates that applying BPI GA's quality strategy in emerging markets can create value. The performance improvement is illustrated by an increase in risk-reward ratio from 0.17 (BOVA11) to 1.03 (Quality Strategy) in Real terms. Moreover, the flight to quality phenomenon may suggest that quality strategies outperform other investment strategies used in the Brazilian market as they perform well in volatile and uncertain markets.[6] These findings confirm the effectiveness of quality investing strategies in emerging markets and are in line with findings by Mackenzie (2021), suggesting great potential for style investing strategies in this space. Nevertheless, it should be noted that the exposure to non-Brazilian equity might partly explain the difference in returns. Hence, a different benchmark might be better suited to identify the strategy's effectiveness. Furthermore, the strategy tested may suffer from a survivorship bias as the investment universe comprises only those companies that survived the past eleven years and omits those that failed during the period (Appendix 4, Appendix 7).

Evidence suggests that quality investing strategies may perform better when applied to other stock universes. The risk-reward ratio achieved with the quality strategy is considerably lower than the one achieved when applying the same strategy- including exclusion and picking the top 50 quality stocks- to the MSCI World (risk-reward ratio of 1.3).[7] Thus, it can be concluded that while BPI GA's quality strategy creates value, its effectiveness varies and is contingent on the investment universe it is applied to. The size of the investment universe may significantly impact the strategy's effectiveness. While the MSCI World comprises about 1750

---

[6] Investors flock to quality companies in times of uncertainty, thereby increasing the quality premium.
[7] For further information reference collective group thesis

companies, the stock universe used to test the strategy with Brazilian equity comprises 593 stocks. Additionally, the poor state of the Brazilian economy over the tested period and the low number of companies with high profitability- the main trait of quality companies- may have hurt the strategy. Therefore, BPI GA should consider applying the strategy to a larger investment universe with exposure to countries with positive economic development.

8.2.2 Factor Analysis

The quality strategy exhibits exposure to the quality factor CMA and the market. In line with the focus of Brazilian companies on funding investments through retained earnings, an exceptionally high positive exposure to the factor associated with conservative investing as well as a large market coefficient is observed. Furthermore, the strategy turns the negative and significant RMW coefficient- observed in the Brazilian market- to insignificant, thereby increasing the exposure to the quality premium. As a result, much of the strategy's returns are driven by exposure to the quality factor- associated with conservative investing- and the market. Moreover, the positive, statistically significant CMA coefficient suggests the existence of the quality premium in Brazil. However, no exposure to the main quality factor, the profitability factor robust minus weak, can be observed. This indicates that BPI GA's quality strategies may fail to achieve their full potential in the tested stock universe. The lack of exposure to the factor RMW may be explained by the low number of Brazilian companies that are highly profitable. Hence, it can be concluded that a quality premium is observed in the Brazilian market, but it may be weaker given the lack of exposure to the profitability factor (Appendix 8).

8.3 Analysis of the Quality Equity Screen

8.3.1 Analyzing the Evidence of Quality Companies

The purpose of this exercise is to determine whether there are sufficient quality companies at any given point in time during the analyzed period. By comparing the number of securities passing the equity screen relative to the size of the stock universe, one can see that the share of MSCI World constituents passing the screen is larger than the Brazilian one. Hence, there is strong evidence that the Brazilian equity market may have relatively fewer quality companies. Moreover, it can be inferred that there are insufficient quality companies in the Brazilian stock universe to fully leverage the potential of quality investing strategies as the quality strategy tested holds 25 securities at any given point in time. These findings point to the fact that BPI GA should expand its investment universe beyond the Brazilian market when pursuing quality investing strategies in emerging markets (Appendix 9, Appendix 10).

8.3.2 Performance Analysis

The poor performance of the equity screen may be traced back to the strategy's exposure to specific industries. This poor performance is illustrated by risk-reward ratios of 0.22 (BOVA11) and 0.19 (Quality Equity Screen) in Real terms. A lower number of holdings is associated with higher volatility. However, the strategy exhibits below-market volatility and below-market returns. The low returns may be explained by the strategy's high exposure to companies from the service and industrial production sectors, which have performed particularly badly since 2016 (OECD 2021). Conversely, the reduced volatility may be explained by the fact that the applied criteria excluded companies with a weak balance sheet and lower profitability- companies that are more prone to volatility (Appendix 4).

8.3.3 Factor Exposure Analysis

The equity screen returns exhibit a value tilt. The value factor is inversely related to the main quality factor robust minus weak- exhibiting a correlation of -0.48 with the RMW factor. Conversely, the value factor is positively correlated with the second quality factor, CMA (correlation of 0.55) (Appendix 12). Thus, the strategy is expected to reduce exposure to the quality factor RMW while increasing exposure to the factor CMA. However, no statistically significant exposure to CMA or a statistically significant and negative coefficient RMW is observed. In contrast, the overall market exhibits exposure to the CMA and a statistically significant, negative RMW coefficient. This exposure to the value factor may be explained by the strategies overweight on the industrial sector, which has a strong value tilt. Conversely, the lack of significant RMW and CMA coefficients may partly be explained by the relatively low adjusted R-squared of 0.57. The low R-squared suggests that the factor analysis should be analyzed with caution as the model's explanatory power is limited. Nevertheless, considering the poor performance of the equity strategy and the lack of exposure to quality factors, BPI GA should refrain from using this method in emerging markets (Appendix 11).

8.4 Comparing Strategies and the Market

BPI GA's quality strategy performs the best in a majority Brazilian stock universe. Comparing the two tested strategies and the performance of the Brazilian market, the quality strategy generates the highest risk-adjusted returns. This is illustrated by a risk-reward ratio of 1.03, 0.22, and 0.19 in Real for the quality strategy, the market, and the equity screen respectively. Equally, the quality strategy outperforms other strategies in USD denoted returns, exhibiting a risk-reward ratio of 0.18, compared to the market (–0.17) and the equity screen (-0.24). Hence, the quality strategy increased returns by 10.15% (Real) and 9.73% (USD) while also reducing volatility by 10.15% (Real) and 11.78% (USD). Thus, it can be concluded that the quality strategy would have provided BPI GA with the highest risk-adjusted returns over the analyzed period from 2012 to 2021. Moreover, the substantial difference in USD and Real denominated returns suggests that hedging Real exposure may make investments in Brazil more attractive for BPI GA (Appendix 4).

The regression analysis supports the use of BPI GA's quality strategy. Comparing the quality strategy to the market, an increase of the quality coefficient conservative minus aggressive from 0.66 to 1.06 is observed, while the main quality factor robust minus weak turns from statistically significant and negative to insignificant. Thus, the factor and performance analyses suggest that BPI GA should choose the quality strategy over the market or equity screen when investing in Brazil (Appendix 6, Appendix 8).

Figure 1: Cumulative Returns of different Strategies in BRL

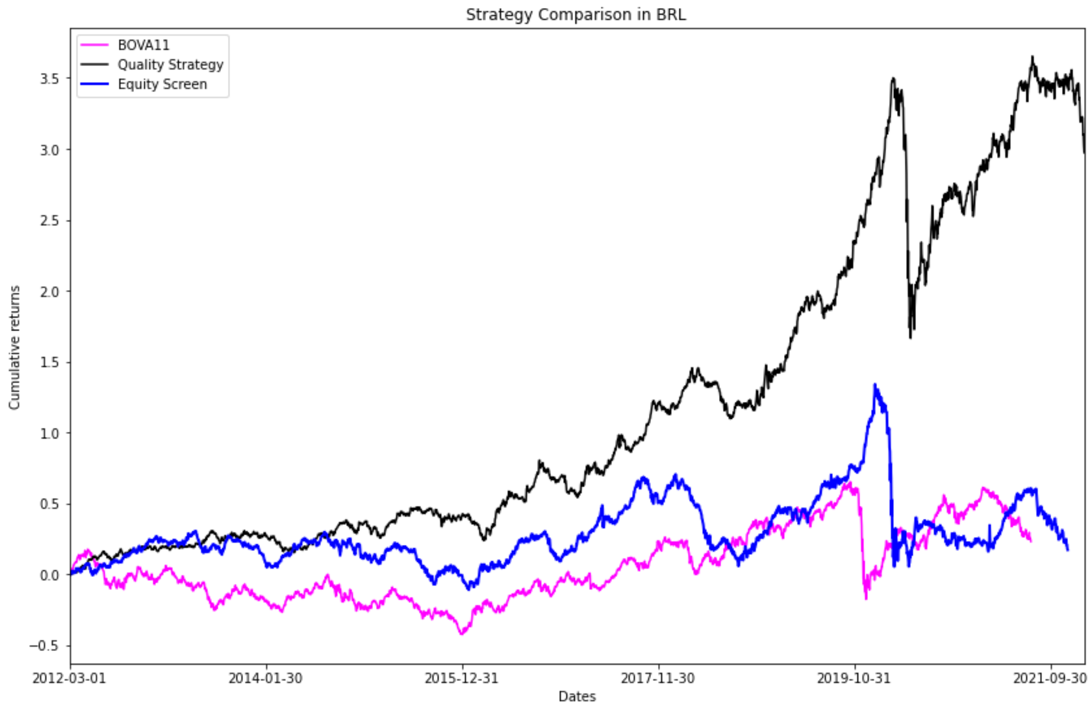


Figure 1 depicts the cumulative returns of BPI GA's quality strategy, the quality equity screen, and BOVA11 between January 2012 and September 2021 denominated in Real. The graph illustrates the outperformance of the quality strategy.

Figure 2: Cumulative Returns of different Strategies in USD

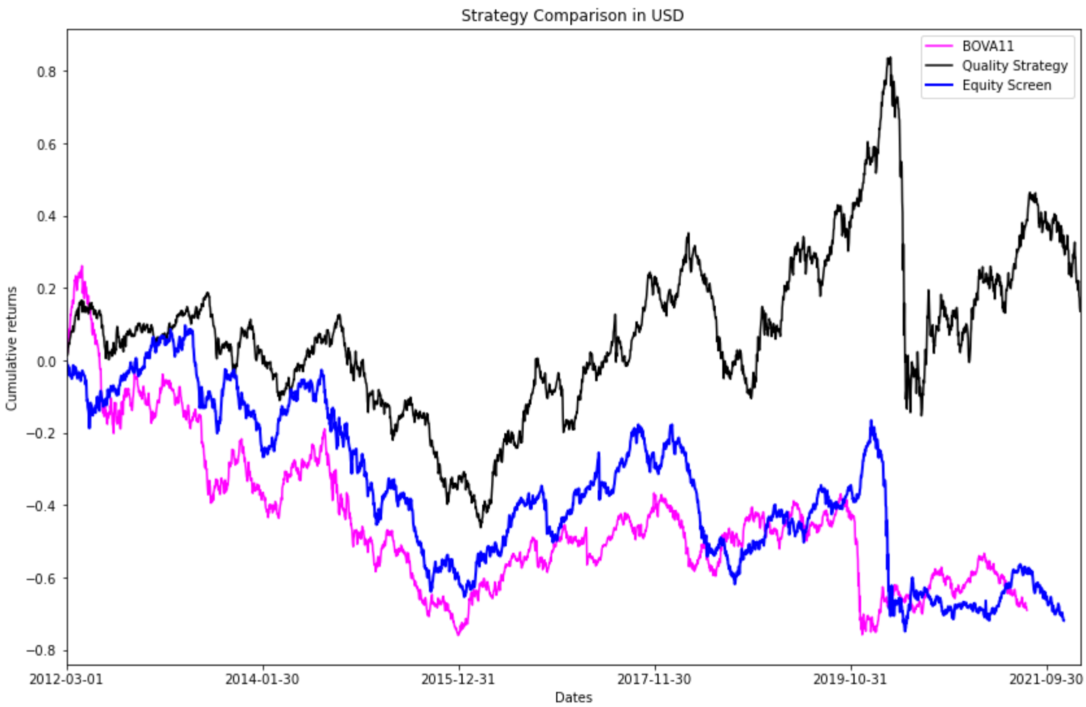


Figure 2 depicts the cumulative returns of BPI GA's quality strategy, the quality equity screen, and BOVA11 between January 2012 and September 2021 denominated in USD. The graph illustrates the outperformance of the quality strategy.

8.5 Limitations and future research

While the findings of this thesis suggest that applying BPI GA's quality investing strategy to a majority Brazilian equity universe creates value, some of the findings have to be analyzed with caution. Currency effects and a lack of suitable factors may limit the explanatory power of the factor analysis. The factor analysis results presented in this paper may be skewed as regressions are exclusively run in USD denominated returns. However, as highlighted across all strategies analyzed, currency effects have a powerful impact on returns generated. Hence, there is a high likelihood that foreign exchange effects skew the regression results. Moreover, the emerging market Fama French factors used in the analysis lack a specific geographic focus on Latin America. Bloomberg's Latin American factors were used to address the issue. However, confirming the validity of the factors was not possible. It was decided not to use the factors as the lack of style indices in Latin America prevented robustness tests and inconsistent regression results likely caused by the factors "tutti-frutti"[8] returns decreased the confidence in the model.

Furthermore, the returns of the quality strategy may be overstated as the backtest may be affected by survivorship bias. Finally, the Brazilian equity market does not constitute the correct benchmark for the quality strategy as its exposure to Brazil is only 70%. Considering the horrific performance of the Brazilian equity market relative to its peers, this may well overstate the relative performance of the quality strategy.

Future research should test quality strategies on larger investment universes, use geographically focused factor models and avoid survivorship bias through the use of investment universes with changing constituents. Increasing the investment universe will allow for an increase in holdings in the quality investing strategy, likely leading to a decrease in the strategy's volatility. Moreover, a larger investment universe will enable investors to incorporate exclusion criteria, identifying quality companies more reliably. The use of factor models with returns denominated in the local currency will provide more reliable regression results. Equally, research on the implementation of foreign exchange hedges in quality investing strategies may prove to be fruitful given the volatility of many emerging market currencies. Furthermore, the use of dynamic investment universes and the use of the proper benchmark will allow for a better evaluation of the strategies. Finally, it might be interesting to compare emerging market quality strategy returns from different regions and macro-economic environments to confirm that the flight to quality phenomenon holds in emerging markets and determine whether the quality strategies perform consistently across all emerging market countries.

[8] Returns from a given country are not converted into a common currency

9. Conclusion

BPI GA's quality investing strategy may be successful in emerging markets. This master contributes to research by (1) confirming the value of BPI GA's quality investing strategy in emerging markets, (2) proving the existence of the quality premium in Brazil, (3) providing evidence suggesting a low number of quality companies in Brazil, (4) illustrating that BPI GA’s quality strategy performance is sensitive to the size of the investment universe it is applied to and (5) providing evidence of the inefficiency of quality equity screens in emerging markets.

Backtesting BPI GA's quality strategies on a majority Brazilian equity investment universe, it was confirmed that the quality investing strategy creates value in emerging markets. The quality investing strategy increased the risk-reward ratio- denominated in Real- from 0.22 to 1.03. Nonetheless, these results must be analyzed with caution. The Brazilian market does not constitute the perfect benchmark for the tested strategy, and the investment universe used may suffer from survivorship bias.

Moreover, BPI GA's quality strategy returns exhibit a strong exposure to the quality factor conservative minus aggressive. Hence, the existence of a quality premium in the Brazilian market was confirmed. Nevertheless, the lack of exposure to the main quality factor robust minus weak suggests that Brazil's quality premium may be low. This may indicate that BPI GA's quality strategy will fail to achieve its full potential in Brazil. Additionally, the significant effects of currency conversion may limit the explanatory power of the regression results.

Furthermore, evidence suggests that the Brazilian equity market may have too few quality companies. The lower number of quality companies has implications for the performance of the BPI GA’s quality strategy. While applying the quality strategy to the majority Brazilian stock universe produced a risk-reward ratio of 1.03, applying the same strategy to the MSCI World produces a risk-reward ratio of 1.3. Thus, there is evidence that the size of the stock universe and the number of quality companies in a universe affect the strategy's performance. Hence, it is recommended that BPI GA applies its quality strategy to a larger emerging market investment universe.

Finally, the quality equity screen does not create value when applied to emerging equity markets. The quality equity screen risk-reward ratio denominated in Real and USD is lower than the one of the market. Hence, BPI GA should refrain from applying the quality equity screen in the Brazilian market.

The evidence found in this thesis confirms the hypothesis that quality investing, following BPI GA's approach, creates value in emerging markets. Moreover, it highlights the great potential of applying BPI GA's quality investing strategy in emerging markets. These findings are relevant as emerging markets are projected to overtake the developed world by size in 2035 (Morgan Stanley 2021). Hence, focusing on developing a compelling emerging market investment offering may provide BPI GA with a competitive advantage in the foreseeable future.

10. Bibliography

Barbosa, Fernando, Marco Bonomo, Joao De Mello, and Lira Mota. 2019. *Short-Selling Restrictions and Returns: A Natural Experiment.* 01 05.

Black, Fischer. 1972. "Capital Market Equilibrium with Restricted Borrowing." *The Journal of Business* 444-455.

BlackRock. 2018. *www.blackrock.com.* 05 01. Accessed 12 03, 2021. https://www.blackrock.com/us/individual/investment-ideas/what-is-factor-investing.

Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 57-82.

Fama , Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 427-465.

Fama, Eugene F., and Kenneth R. French. 2015. "A five-factor asset pricing model." *Journal of Financial Economics* 1-22.

Foye, James. 2018. "A comprehensive test of the Fama-French five-factor model in emerging markets." *Emerging Market Review* 199-222.

French, Kenneth R. 2021. *Kenneth R. French.* 31 10. Accessed 11 15, 2021. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5emerging.html.

Hsu , Jason , Vitali Kalesnik, and Engin Kose. 2019. "What Is Quality?" *Financial Analysts Journal* (CFA Institute) 44-61.

Lee, Joey. 2010. *Changing Spaces: Emerging Markets Investing.* Industry Research, Greenwich: AQR Capital Management.

Leite, André Luis , Marcelo Cabus Klotzle, Antonio Carlos Figueiredo Pinto, and Aldo Ferreira da Silva. 2018. "Size, value, profitability, and investment: Evidence from emerging markets." *Emerging Market Review* 45-95.

Lintner, John. 1965. “Security Prices, Risk, and Maximal Gains From Diversification.” *The Journal of Finance* 587-615.

Mackenzie Investments. 2021. *A quantitative approach to emerging markets equity.* Industry Research, Toronto: Mackenzie Investments.

Morgan Stanley. 2021. *www.morganstanley.com.* 08 02. Accessed 12 04, 2021. https://www.morganstanley.com/im/en-la/intermediary-investor/insights/articles/emerging-market-allocations-how-much-to-own.html.

Nielson, Darby , Frank Nielsen, and Bobby Barnes. 2016. *An Overview of Factor Investing* . Industry Research, Boston: Fidelity Institutional Asset Managemen.

Novy-Marx, Robert. 2013. “The other side of value: The gross profitability premium.” *Journal of Financial Economics* Pages 1-28.

OECD. 2019. *Equity Market Development in Latin America.* Industry Research, Paris: OECD.

—. 2021. *www.oecd.org.* 01 12. Accessed 12 02, 2021. https://www.oecd.org/economy/brazil-economic-snapshot/.

Petersen, Mitchell A. 2009. “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches .” *The Review of Financial Studies* 435-480 .

Ross, Stephen A. 1976. “The valuation of options for alternative stochastic processes.” *Journal of Financial Economics* 145-166.

Sharpe, William F. 1964. “Capital asset prices : A theory of market equilibrium under conditions of risk.” *Journal of Finance* 425-442.

Wagstyl, Stefan. 2010. *www.ft.com.* 08 09. Accessed 12 11, 2021. https://www.ft.com/content/ca09873c-bb6c-11df-a136-00144feab49a.

11. Appendix

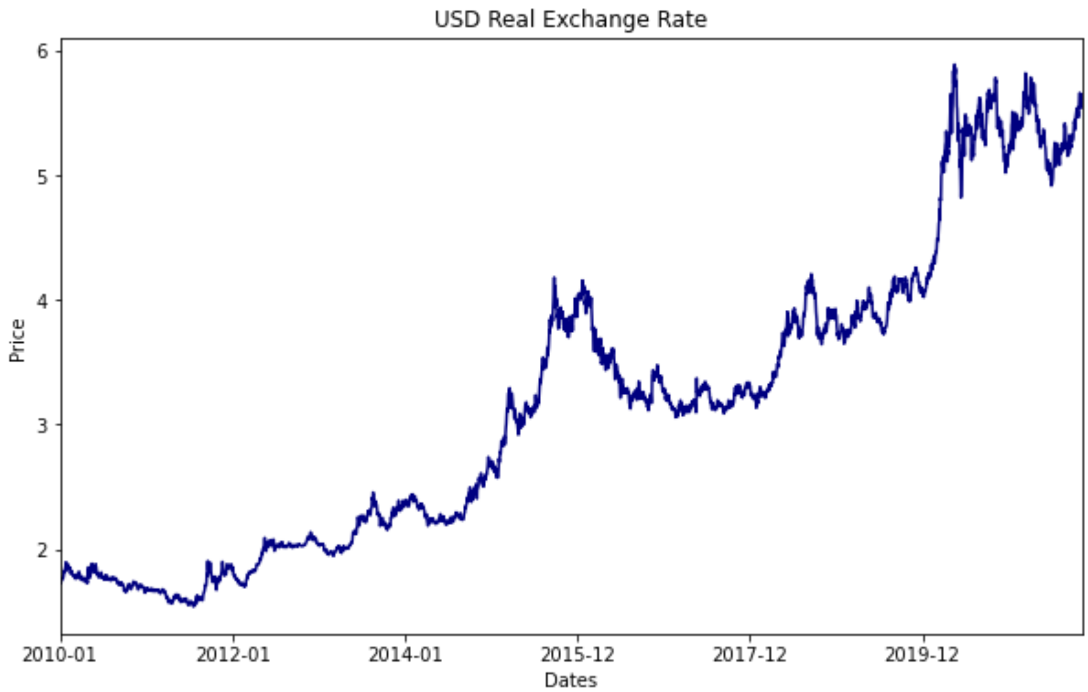
Appendix 1: Robustness Test Fama French Factors

	Fama French Robustness Test:		
	Value	Size	Quality
const	-0.005***	-0.005***	-0.002**
	(0.001)	(0.001)	(0.001)
MKT-RF	1.011***	1.038***	1.050***
	(0.015)	(0.035)	(0.018)
CMA	0.208***	-0.193	0.320***
	(0.056)	(0.129)	(0.067)
HML	0.285***	0.222**	-0.014
	(0.044)	(0.102)	(0.052)
RMW	-0.037	0.019	0.114*
	(0.056)	(0.129)	(0.067)
SMB	-0.244***	0.791***	-0.012
	(0.038)	(0.088)	(0.046)
Observations	121	121	121
R^2	0.987	0.935	0.980
Adjusted R^2	0.987	0.932	0.979

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

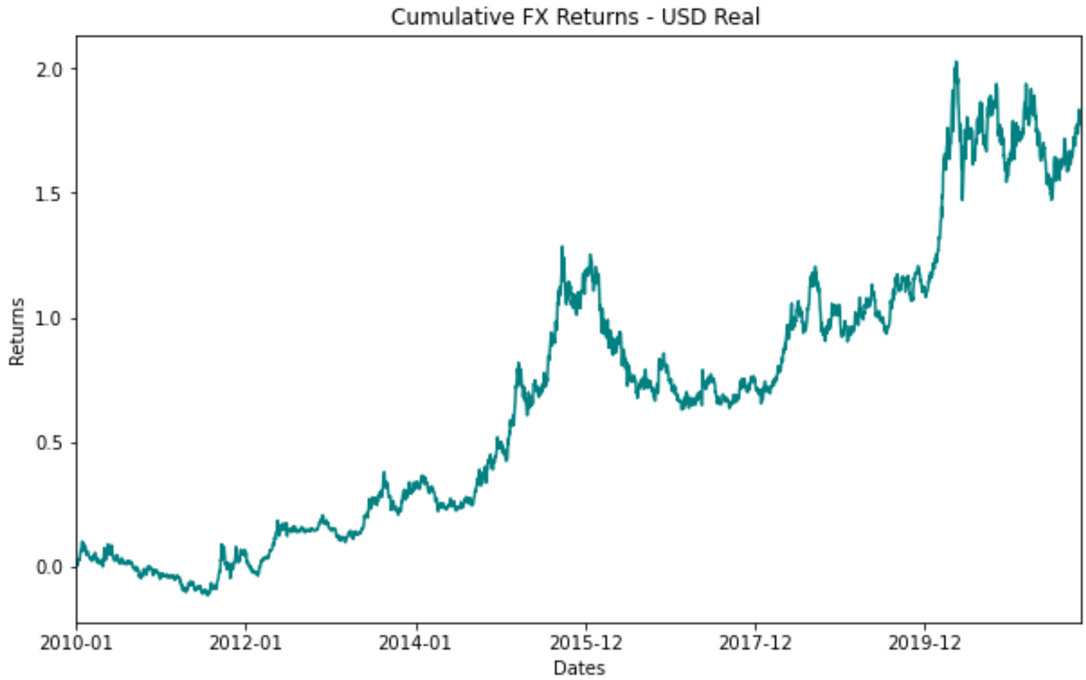
Appendix 1 depicts the regression results of the Fama French factor robustness test between August 2011 and September 2021. The test regressed the Fidelity Emerging Markets Quality Income Index, MSCI Emerging Markets Value Weighted Index, MSCI Emerging Markets Small-Cap ETF onto the Fama French model. The results suggest the validity of the Fama French factors.

Appendix 2: USD Real Exchange Rate 2010- 2021



Appendix 2 depicts the development of the USD to Brazil Real exchange rate between January 2010 and September 2021. The graph illustrates the decay of the Brazilian Real.

Appendix 3: Cumulative Foreign Exchange Returns USD Real 2010- 2021



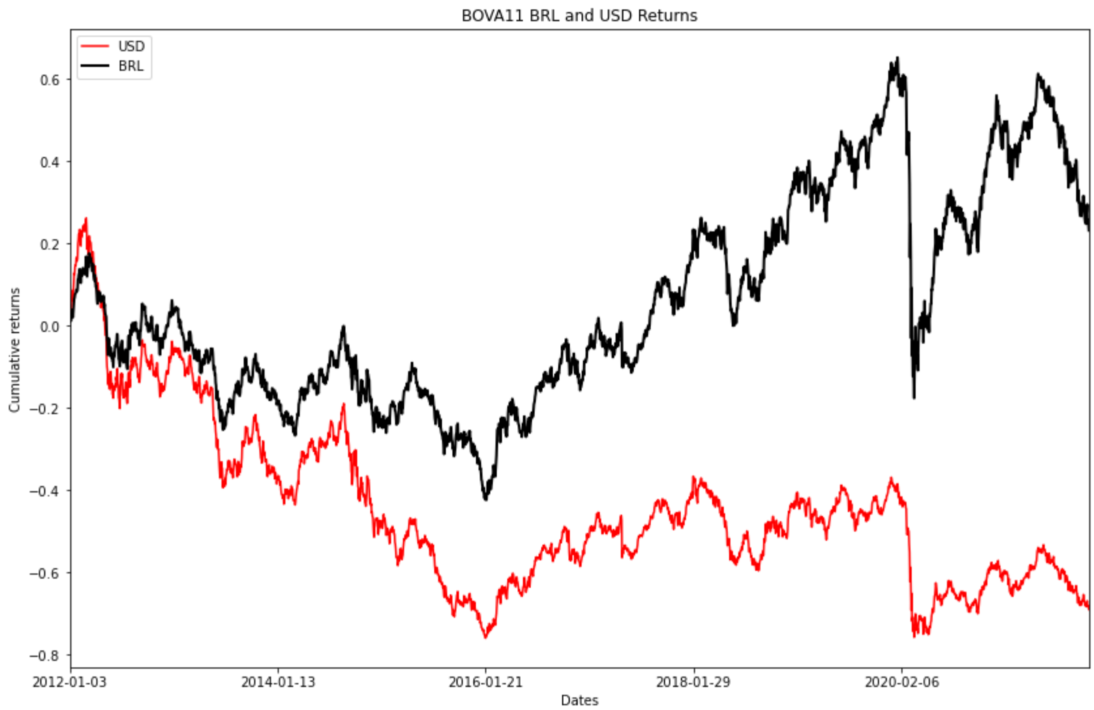
Appendix 3 depicts the cumulative returns that a Brazilian investor would have generated by investing in USD between January 2010 and September 2021. The graph is further evidence of the decay of the Brazilian Real.

Appendix 4: Strategy Performance Statistics

	BOVA11 BRL	BOVA11 USD	Quality BRL	Quality USD	Equity Screen BRL	Equity Screen USD
Average Return	5.62%	-5.72%	15.77%	4.01%	4.13%	-7.41%
Standard Deviation	25.54%	34.66%	15.33%	22.88%	21.88%	30.58%
Info Sharpe	0.22	-0.17	1.03	0.18	0.19	-0.24
Positive Days	51.72%	51.20%	54.08%	51.80%	52.21%	50.38%
Daily Skew	-0.50	-0.41	-1.20	-0.90	-0.97	-0.88
Daily Kurtosis	10.20	7.26	17.71	11.06	24.56	12.73
Daily Max	13.40%	14.37%	6.36%	8.58%	14.54%	12.90%
Q3	0.93%	1.19%	0.56%	0.75%	0.68%	0.92%
Med	0.05%	0.05%	0.06%	0.05%	0.00%	0.00%
Q1	-0.83%	-1.19%	-0.41%	-0.68%	-0.59%	-0.93%
Daily Min	-14.57%	-17.64%	-10.46%	-13.83%	-15.85%	-19.50%
Max drawdown	-57.57%	-129.29%	-46.38%	-68.91%	-67.17%	-96.70%

Appendix 4 depicts the performance statistics of the different strategies backtested between January 2010 and September 2021. The strategies are presented in USD and Brazilian Real.

Appendix 5: Cumulative Returns BOVA11 in USD and BRL



Appendix 5 depicts the cumulative returns of BOVA11 (the Brazilian market) between January 2012 and September 2021. The graph illustrates how USD and Real returns differ significantly.

Appendix 6: Regression Table BOVA11

	BOVA11 on Fama French	
	CAPM	FF5-Factor
const	-0.014**	-0.012**
	(0.006)	(0.006)
MKT-RF	1.599***	1.360***
	(0.168)	(0.181)
CMA		0.665**
		(0.327)
HML		1.012**
		(0.464)
RMW		-1.067**
		(0.523)
SMB		-0.518
		(0.399)
Observations	140	140
R^2	0.620	0.722
Adjusted R^2	0.618	0.712
Residual Std. Error	0.062(df = 138)	0.054(df = 134)
F Statistic	91.015*** (df = 1.0; 138.0)	63.554*** (df = 5.0; 134.0)

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Appendix 6 depicts the regression results of the BOVA11 ETF onto the Fama French factors between January 2010 and September 2021. Significant exposure to the market (1.36), CMA (0.67), HML (1.01), and RMW (-1.01) can observe.

Appendix 7: Cumulative Returns Quality Strategy in USD and Real

Appendix 7 depicts the cumulative returns of BPI GA's quality strategy between January 2012 and September 2021. The graph illustrates how USD and Real returns differ significantly.

Appendix 8: Regression Table Quality Strategy

	Quality on Fama French:	
	CAPM	FF5-Factor
const	-0.004	-0.005
	(0.006)	(0.006)
MKT-RF	1.221***	1.188***
	(0.184)	(0.196)
CMA		1.056***
		(0.401)
HML		0.390
		(0.436)
RMW		-0.087
		(0.360)
SMB		-0.093
		(0.380)
Observations	117	117
R^2	0.560	0.644
Adjusted R^2	0.556	0.627
Residual Std. Error	0.050(df = 115)	0.046(df = 111)
F Statistic	44.185*** (df = 1.0; 115.0)	27.116*** (df = 5.0; 111.0)
Note: Standard errors in parentheses.		*p<0.1; **p<0.05; ***p<0.01

Appendix 8 depicts the regression results of BPI GA's quality strategy onto the Fama French factors between February 2012 and September 2021. Significant exposure to the market (1.19) and CMA (1.06) can be observed.

Appendix 9: Brazilian Quality Holdings

Brazil	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Avg
Total Holdings	249	246	225	197	201	219	222	249	282	334	242
Passed Screen	12	13	16	10	11	15	14	13	5	23	13
Share	4.8%	5.3%	7.1%	5.1%	5.5%	6.8%	6.3%	5.2%	1.8%	6.9%	5.5%

Appendix 9 depicts the number of Brazilian companies that have passed the quality equity screen between 2012 and 2021. The Total Holdings row indicates the number of publicly traded companies in a given year, the Passed Screen the number of holdings that passed the screen, and Share the percentage of companies that passed the screen.

Appendix 10: MSCI World Quality Holdings

MSCI World	2015	2016	2017	2018	2019	2020	2021	Avg.
Total Holdings	1712	1730	1815	1858	1823	1683	1788	1772.7
Passed Screer	141	142	150	164	183	138	193	158.71
Share	8.2%	8.2%	8.3%	8.8%	10.0%	8.2%	10.8%	8.9%

Appendix 10 depicts the number of MSCI World companies that passed the quality equity screen between 2015 and 2021. The Total Holdings row indicates the number of publicly traded companies in a given year, the Passed Screen the number of holdings that passed the screen, and Share the percentage of companies that passed the screen.

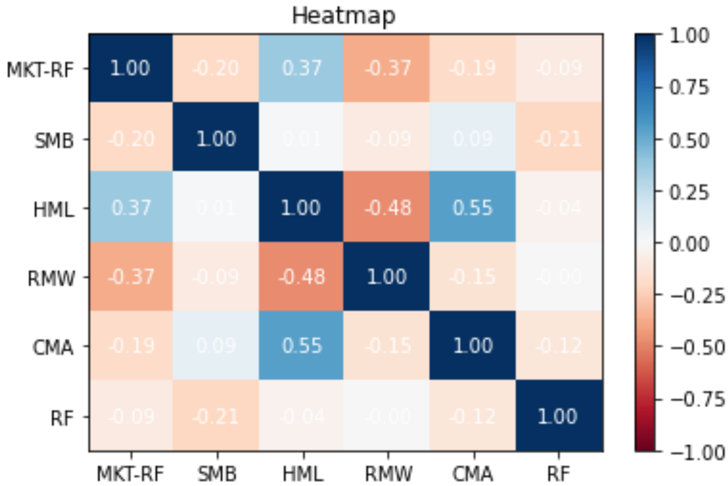
Appendix 11: Regression Table Quality Equity Screen

	Equity Screen on Fama French:	
	CAPM	FF5-Factor)
const	-0.013*	-0.016**
	(0.008)	(0.008)
MKT-RF	1.578***	1.436***
	(0.258)	(0.273)
CMA		0.178
		(0.725)
HML		1.139*
		(0.622)
RMW		0.242
		(0.571)
SMB		0.255
		(0.536)
Observations	115	115
R^2	0.509	0.568
Adjusted R^2	0.505	0.548
Residual Std. Error	0.070(df = 113)	0.067(df = 109)
F Statistic	37.443*** (df = 1.0; 113.0)	24.329*** (df = 5.0; 109.0)

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Appendix 11 depicts the regression results of the quality equity screen onto the Fama French factors between April 2012 and September 2021. Significant exposure to the market (1.44) and HML (1.14) can be observed.

Appendix 12: Correlation Heatmap Fama French Factors



Appendix 12 depicts the correlation heatmap of the Fama French factors between January 2010 and September 2021.