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School of Business and Management
Strategic Finance and Analytics

Master's Thesis

The Performance of Factor Investing during the Covid-19 crisis: Evidence from the U.S. and European Stock Markets

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Tämä tutkimus tutkii faktorisijoittamisen suoriutumista Covid-19 kriisissä vuoden 2020 alusta, käsittäen ensimmäiset 6 kuukautta kriisin ajalta. Tutkimus on toteutettu vahvan akateemisen perustan omaaville faktoreille, jotka ovat arvo (e.g., Fama ja French 1993), koko (e.g., Banz 1981), momentum (e.g., Jegadeesh ja Titman 1993), laatu (e.g., Sloan 1996) ja näiden lisäksi vähemmän tutkittu faktori ESG on myös sisällytetty tutkimukseen. Faktoreiden suoriutumista tutkitaan kolmella eri aikaperiodilla, kattaen laskumarkkinan, nousumarkkinan sekä koko 6 kuukauden aikaperiodin holistisen näkökulman saamiseksi. Faktoreiden suoriutumista tutkitaan 20 eri faktori-indeksillä sekä sijoittajan käytännössä saamaa tuottoa 20 eri ETF:llä, jotka seuraavat kyseisiä faktori-indeksejä. Lisäksi 32 *"puhtaampaa"* faktoriportfoliota muodostetaan hyödyntäen parhaita käytäntöjä akatemiasta ja portfolioiden suoriutumista verrataan faktori-indeksien suoriutumiseen. Puhtaammat faktoriportfoliot on muodostettu hyödyntäen sekä tasa- että markkinapainotettuja metodologioita ja lisäksi soveltaen long-short ja long-only strategioita. Näiden portfolioiden tavoitteena on saada aikaan puhtaampi, läpinäkyvämpi ja korkeampi faktori altistuminen ilman erilaisia metodologiaan tai likviditeettiin pohjautuvia rajoituksia, jotka ovat läsnä faktori-indekseissä ja ETF:issä. Kirjallisuuskatsauksessa muodostetaan hypoteesit faktoreiden suoriutumiselle Covid-19 kriisissä pohjautuen faktoreiden suoriutumiseen edellisten kriisien aikana.

Tutkimustulosten mukaan faktorit pärjäsivät odotetusti suhteessa muodostettuihin hypoteeseihin. Ainoastaan momentum-faktori tuotti korkeampia tuottoja kaikilla aikaperiodeilla. Maantieteellisesti katsottuna eurooppalaisten faktori-indeksien tuotot laahasivat Yhdysvaltoihin sijoittavien faktori-indeksien perässä, erityisesti nousumarkkinalla. Kun faktoreiden suoriutumista mitataan koko aikaperiodilla, arvo faktori-indeksit menestyivät keskimäärin heikoiten, sen jälkeen tulivat koko, laatu, ESG ja momentum. Erot keskiarvotuotoissa eivät olleet kuitenkaan tilastollisesti merkitseviä Welchin t-testin perusteella. Kaikki faktori-ETF:t alisuoriutuivat suhteessa seurattaviin faktori-indekseihin, kun tutkitaan todellista tuottoa, jonka sijoittaja voi saada faktorituotteisiin sijoitettaessa. ETF:ien tracking error oli korkein koko-faktori kategoriassa ja matalin arvo-faktori kategoriassa. Faktoreiden performanssia voidaan selittää indeksien metodologioilla, sektoriperformanssilla, sektoriallokaatioilla sekä suhteellisen arvonmäärityksen mittareilla. Suhteellinen arvonmääritys paljasti selkeän yhteyden EPS estimaattien ja indeksien tuottojen välillä. Lisäksi kaikilla indekseillä tapahtui kasvua P/E-kertoimen osalta Covid-19 kriisin aikana. Tämä tutkimus tuotti kvantitatiivisesti evidenssiä sektoriperformanssin ja allokaatioiden kontribuutiosta ETF:ien kokonaistuottoihin. Korrelaatiot faktoreiden välillä olivat suhteellisen korkeita ennen kriisiä, mutta laskivat hieman kriisin aikana. Yleisesti ottaen *"puhtaampien"* markkina- ja tasapainotettujen long-only portfolioiden tuotto oli heikompaa verrattuna tutkittuihin faktori-indekseihin. Tutkimuksen mukaan tämä indikoi, että faktoripreemiot ovat kompensaatiota korkeamman riskin ottamisesta.

ABSTRACT

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This thesis studies the performance of factor investing during the Covid-19 crisis from the beginning of 2020, covering approximately the first six months of the crisis. The study is conducted for academically-grounded factors including value (e.g., Fama and French 1993), size (e.g., Banz 1981), momentum (e.g., Jegadeesh and Titman 1993), and quality (e.g., Sloan 1996). In addition, a newer and less academically-grounded factor ESG is included as well. The performance of factors is studied over three different time periods, comprising the bear market, the recovery market, and the full 6 months period to achieve a holistic view. The performance of factors is examined with 20 different factor indices, and the practical, actual performance achievable by investors is examined with 20 ETFs following those indices. In addition, 32 pure factor portfolios are constructed by utilizing the best practices derived from academia to benchmark the performance of factor indices. Pure factor portfolios consist of both market- and equally-weighted methodologies, as well as long-short and long-only strategies. The objective of pure factor portfolios is to obtain a purer, more transparent, and higher factor exposure, without any methodology or liquidity based restrictions as with factor indices and ETFs. In the literature review, hypotheses are formed based on the historical performance of factors during the preceding crises to identify whether the factors perform correspondingly during the Covid-19 crisis.

According to the results, factors performed relatively in line with the hypotheses formed from academia except the momentum factor, which produced higher returns in all periods. Geographically, the European factor indices lagged the U.S. counterparts thoroughly, especially during the recovery phase. The value factor indices had the poorest performance on average, followed by size, quality, ESG, and momentum when the performance of factors is considered during the full sample period. However, the differences in mean returns of the samples were not statistically significant, according to Welch's t-test. All factor ETFs underperformed their benchmark factor indices when the practical performance of actual investable factor products is considered. The tracking error of ETFs was highest in the size factor category and lowest in the value factor category. The performance of the factors can be explained by the methodology of indices, the sector performance, allocations as well as by relative valuation metrics. Relative valuation revealed a clear relationship between the EPS estimates and the return of factor indices. All indices had some expansion in P/E multiple during the Covid-19. This thesis quantitatively provides evidence that sector performance and allocations significantly contribute to the total returns of ETFs. The correlations between factors were relatively high before the crisis but slightly decreased during the crisis. In general, when the performance of pure factor portfolios is considered, the market capitalization-weighted-, as well as equally-weighted long-only pure factor portfolios produced inferior returns compared to the examined factor indices. According to this study, purer factor tilt decreased the returns, indicating that factor premiums are compensation for taking a higher risk.

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I would be lying if I said that I am not proud of myself. The great journey at LUT is becoming to an end, and the word *gratitude* describes my state of mind at the moment. It has been a great honor to study at LUT and develop myself with new information and skills in the field of finance and analytics, which I enjoy the most. In addition, I have been very fortunate since I have met great people during this journey and made lifelong friendships.

I would like to express the sincerest gratitude to the following people when it comes to this Master's thesis. First, I would like to thank Professor Eero Pätäri for guiding this research and Professor Sheraz Ahmed for everything that I have learnt from him. Both of these professors have inspired me during my journey at LUT. Second, I want to thank Saku Sairanen and Santtu Saijets for sharing their expertise and offering this great opportunity to complete this thesis for Elo. I am very grateful for all the good ideas and comments that I have received from my supervisors during this thesis. Thirdly, I would also like to say thank you to all the great people I met at Elo during my thesis writing process. Last but not least, I want to thank my fiancé, friends, and family for supporting me during this journey. I want to dedicate this Master's thesis to all of you.

Sincerely,

Henna Louhisto

25th of January 2021, Vantaa

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LIST OF ABBREVIATIONS

APT = *Arbitrage Pricing Theory.*
AUM = *Assets Under Management.*
CAPM = *Capital Asset Pricing Model.*
Covid-19 = *Coronavirus Disease 2019.*
CVS = *Composite Value Score.*
EMH = *Efficient Market Hypothesis.*
EPS = *Earnings Per Share.*
ESG = *Environmental, Social, and Governance*.
ETF = *Exchange-Traded Fund.*
EV/EBIT = *Enterprise Value-to-Earnings before Interest and Taxes.*
EV/EBITDA = *Enterprise Value-to-Earnings before Interest, Taxes, Depreciation, and Amortization.*
EV/SALES = *Enterprise Value-to-Sales.*
FED = *Federal Reserve.*
GICS = *Global Industry Classification Standard.*
ICB = *Industry Classification Benchmark.*
P/B = *Price-to-Book.*
P/E = *Price-to-Earnings.*
ROE = *Return-on-Equity.*
SRI = *Socially Responsible Investing*.
VIX = *Volatility Index.*
WHO = *World Health Organization.*

1. INTRODUCTION

"Factor investing has never been as popular as it is today. However, with the propagation of this type of investment approach, the equity space is becoming increasingly saturated with more and more factors that are ever more removed from academically-grounded research."

- Goltz and Luyten (2019)

On the financial markets, investors are competing with each other in valuing investment instruments and in predicting their performance in order to achieve excess returns. According to Fama's (1970) Efficient Market Hypothesis (EMH), the market already reflects all available information, and thus an investor cannot consistently generate excess returns. The significance of this hypothesis has been challenged numerous times, especially in the context of factor investing (e.g., Banz 1981; Jegadeesh and Titman 1993; Fama and French 1993; Fama and French 2015; Centineo and Centineo 2017).

Factor investing refers to an investment strategy that targets securities that have specific desired attributes, risk premiums, that have been shown to produce excess returns in different time periods and across markets. Factor investing can be essentially subdivided into macroeconomic and style investing. Macroeconomic factors capture broad risks between asset classes whilst style factors explain the returns within the asset class. Style factors are specific, quantifiable characteristics that have been historically shown to produce excess returns compared to other securities in the same asset class. Style factors are strongly connected to equity investing and are extensively studied in academia. In theory, factor investing implicates that investing in firms that have specific factor characteristics should, in the long run, have better risk-adjusted returns compared to the market portfolio. Academic studies have identified several such factors, among which the most established are value, size, and momentum. (Bender, Briand, Melas, and Subramanian 2013; Ang 2014, 213-240) In practice, factor investing is often exercised through exchange-traded funds (ETFs), which consist of a large number of stocks that have desired factor characteristics shown to produce excess returns in the past[1] (Goltz and Le Sourd 2018, 6-16).

[1] In practice, factor investing is often referred as smart beta investing, and the ETF products as smart beta factor ETFs (Ang 2014, 226; Goltz and Le Sourd 2018, 6-16).

In the simplest terms, the excess return is a return that is higher than the return of a comparable market index. If an investor is able to achieve a higher return for the portfolio than the return of a comparable market index, the investor is considered to generate alpha, excess return, or outperform the market in absolute numbers. (CFA Institute 2013, 7, 46; Ang 2014, 307-308; Jacobs and Levy 2014; Centineo and Centineo 2017) On relative terms, the level of risk taken to achieve the excess return should be considered as well. In the field of finance, the risk is often described and measured with volatility, which is the degree of variation or dispersion of instruments' price over time. Standard deviation or variance are statistical measures often used to measure the volatility of an investment. Higher volatility implies a higher risk since the prices are considered to be less predictable compared to less volatile instruments. (Arnott, Hsu and West 2008, 42-43; Ang 2014, 40, 218-222; Korok 2016)

This Master's Thesis will be written for Elo, a Finnish pension insurance company. The research studies the performance of factor investing via various factor indices and ETFs during the Coronavirus disease 2019 (Covid-19) pandemic. Three different time periods during the pandemic are chosen to achieve a holistic view. The first time period is the bear market from the 20th of February 2020 to the 23rd of March 2020, whereas the second time period is the recovery period from the 24th of March 2020 to the 30th of June 2020. The third time period is the full sample period from the 2nd of January 2020 to the 30th of June 2020.

Covid-19 is a global contagious disease caused by a SARS-CoV-2 virus that started to spread at the end of 2019, and already on the 11th of March 2020, the World Health Organization (WHO) stated that Covid-19 is now a global pandemic (World Health Organization 2020a; World Health Organization 2020c). The countermeasures used to control the spread of Covid-19 restricted economic activity, which affected companies and the value of most stocks and indices tumbled down around the world (International Monetary Fund 2020; Bloomberg Terminal 2020). The CBOE Volatility Index, also referred to as VIX by using its ticker symbol, is a popular measure of the stock market's expected volatility. VIX is often used to describe the sentiment of the market and is therefore referred to as the fear index. (Cboe 2019) VIX-index recorded the highest value of all time 82.69 during the Covid-19 on the 16th of March 2020, which was even higher than the value of 80.86 recorded during the great financial crisis on the 20th of November 2008 (Bloomberg Terminal 2020).

This study focuses on the performance of factor investing during the Covid-19 crisis from the beginning of 2020, covering approximately the first six months of the crisis. The aim is to analyze the performance of factor investing during this crisis in comparison to what were the presumptions based on the theoretical background.

1.1 Background and motivation for the research

Factor investing has been in the interest of institutions, private investors, analysts, traders, and academics for decades. The academic foundation of factor investing can be traced back to the 1960s, when the Capital Asset Pricing Model (CAPM) was developed by Treynor (1961, 1962), Sharpe (1964), Lintner (1965a, b), and Mossin (1966). CAPM identified beta as a factor for explaining the relationship between the risk and expected return for an individual stock. Later in the 1970s, Ross (1976) published the Arbitrage Pricing Theory (APT), where he argued that multiple macroeconomic factors explain the returns of stocks. A relatively large amount of academic research on factor investing and different factors began to emerge in the following decades after the foundation of CAPM and APT. For example, Banz (1981) and Rizova (2006) studied the size factor, Haugen and Baker (1991) and Clarke, De Silva, and Thorley (2006) the low volatility factor, Jegadeesh and Titman (1993) and Carhart (1997) the momentum factor, Lakonishok, Shleifer, and Vishny (1994) and Piotroski (2000) the value factor, whereas Novy-Marx (2013) and Asness, Frazzini, and Pedersen (2019) examined the quality factor.

Despite the numerous published academic studies, Eugene Fama's and Kenneth French's (1993) study on factor investing can be considered as a classic and one of the most cited papers in the field of factor investing. In 1993, Fama and French published their study *"Common risk factors in the returns on stocks and bonds"*, where they presented their three-factor model (value, size, and market). The three factors are the outperformance of small versus large companies, the outperformance of high book-to-market versus low book-to-market companies, and the market risk factor.

The interest in factor investing has increased during the 21st century (Centineo and Centineo 2017; Goltz and Le Sourd 2018, 9; Google Trends 2020). Figure 1 represents the relative Google search interest towards factor investing worldwide. The relative Google searches are indexed to start from 0, whereas 100 represents the highest google search activity. Figure 1 shows that the relative interest in factor investing has grown with an upward trend. The search activity related to factor investing started to grow at the end of 2013, and at the time of writing (June 2020), it is at the highest level in its history. (Google Trends 2020)

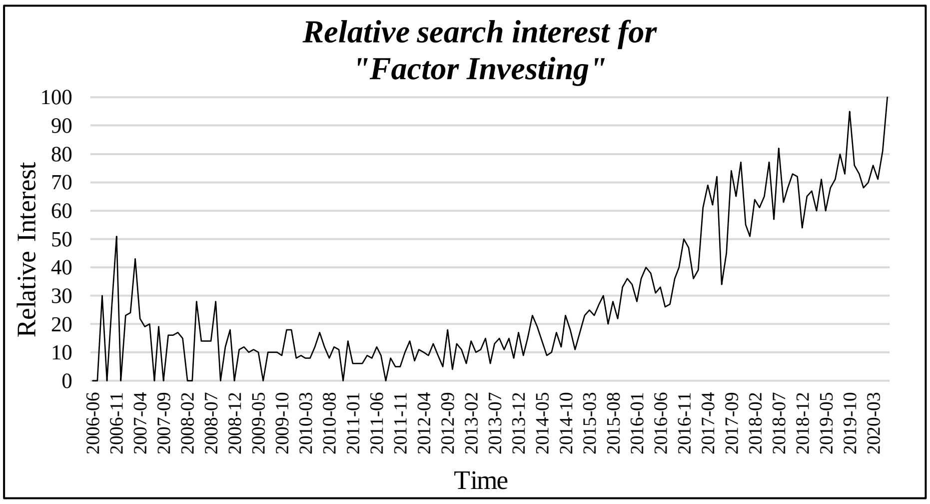

Figure 1. *Relative search interest for "Factor Investing" (Worldwide)*

Factor investing is often practiced throughout exchange-traded funds (Goltz and Le Sourd 2018, 6-16). The roots of exchange-traded funds date back to 1993. ETFs offer the possibility to get diversification benefits without the need to directly invest in multiple stocks. There are active and passive ETFs in the market. Passive ETFs follow prechosen indices, whereas active ETFs are actively managed by portfolio managers. Passive ETFs can follow factor indices, thus making the ETFs to have specific factor characteristics. The management fee of ETFs slightly reduces the return received by the investor compared to the benchmark index, thus increasing tracking error. (Rompotis 2013; Ben-David, Franzoni, and Moussawi 2017)

Figure 2 presents the development of total assets under management (AUM) for equity ETFs and factor ETFs separately (Societe Generale Corporate & Investment Banking 2020). Furthermore, Figure 2 illustrates the development of the number of unique equity and factor ETFs since 2007. Factor ETFs are included in the total number of ETFs as well as in the total AUM of ETFs. As shown in Figure 2, both the number of ETFs and the total AUM of ETFs have rapidly increased from 2007. According to the data provided by the World Bank (2020), the market capitalization of all listed companies in Europe and the United States was approximately 36 trillion U.S. dollars in 2018. This indicates that ETFs investing in Europe and the United States accounted for approximately 8.73% of the total market capitalization. Factor ETFs accounted for 22 % of all ETFs in the U.S. and Europe in 2007, whereas in 2019, the share had increased to 31 percent.

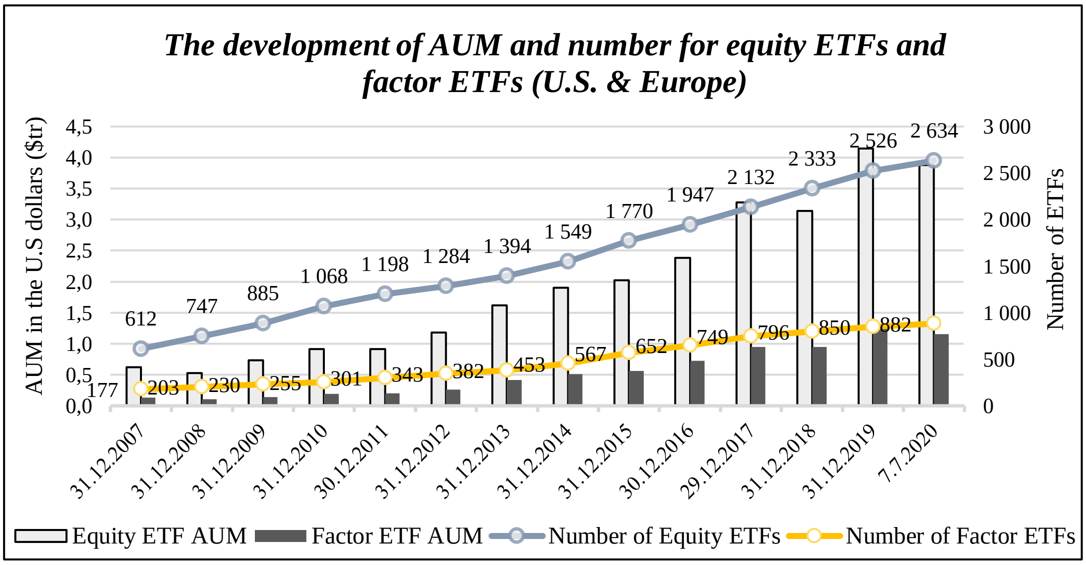

Figure 2*. The development of AUM and number for equity ETFs and factor ETFs (U.S. & Europe)*

There is abundant academic evidence that speaks in favor of factor investing and its ability to generate excess returns (e.g., Banz 1981; Jegadeesh and Titman 1993; Fama and French 1993; Lakonishok et al. 1994; Piotroski 2000; Centineo and Centineo 2017), as well as to get diversification benefits for investors (e.g., Ilmanen and Kizer 2012; Asness, Moskowitz and Pedersen 2013; Centineo and Centineo 2017). On the other hand, there is also conflicting evidence of whether factor investing is able to generate excess returns over the market portfolio in reality. According to Malkiel (2014), the track record of actual factor ETFs, run with real money, is quite spotty on a general level, and only a few funds have been able to outperform the market over the life of the fund. Malkiel (2014) also points out that historical performance is no guarantee of future returns and that the smart beta portfolios have been seen as an object of great marketing operations. Jacobs and Levy (2014) acknowledge that there is much support in the literature for the assertion that there are various factors in addition to CAPM's beta that matter. However, according to Jacobs and Levy (2014), there is less support for the assertion that excess returns can be captured easily and consistently through a simple factor-based approach. In addition, Jacobs and Levy (2014) argue that the security weightings of factor-based strategies are based on historical data, thus resulting in neither dynamic nor forward-looking strategy.

The motivation for this study stems from several different aspects. First, to the best of my knowledge, there is no academic research related to the performance of factor investing during the Covid-19 pandemic. In addition, there are only a handful of studies related to the performance of factor investing during a crisis, and therefore, this thesis contributes to the academic debate with this respect. Factor investing has raised a lot of interest from institutions to private investors, and the AUM and number of factor ETFs have increased rapidly, making the topic important for a wide audience. Finally, there is contradictory evidence related to the actual performance of factor investing.

1.2 Research problem, questions, and objectives

The research problem is to analyze the performance of different factor investment styles during the Covid-19 pandemic. The chosen factors for this study are value, size, momentum, quality, and as a non-traditional and less academically-grounded factor ESG (Environmental, Social, and Governance) is included as well. These studied factors will be presented and discussed in more detail in section two, the literature review and previous findings. Figure 3 illustrates the research problem on a high level from which the research questions are derived for this study.

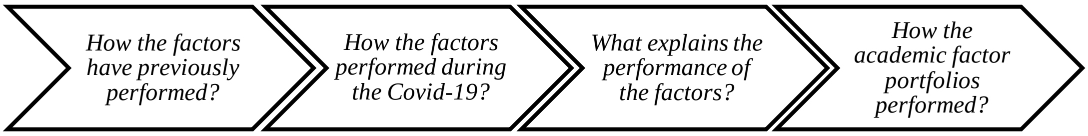

Figure 3. *Illustration of the research problem*

This Master's Thesis will respond to the following two main research questions and two sub-questions to obtain a comprehensive and complementary view of the research subject. The objectives of the research are presented below the research questions. All research questions will be listed and answered in detail in section five, conclusion and discussion.

Question 1. *How factor indices and ETFs performed during the Covid-19 crisis?*

The first research objective is to analyze the performance of factor investing during the first 6 months of the Covid-19 crisis. The Covid-19 crisis is subdivided into three time periods: bear market, recovery market, and the full sample period. The performance is studied in developed markets, more specifically in the U.S. and in Europe. The performance of factor investing is analyzed by studying factor indices as well as ETFs. The performance of factor indices is benchmarked against the market indices, S&P 500 in the U.S. and Stoxx 600 in Europe. Factor ETFs are benchmarked to factor indices, and the tracking error is analyzed. In addition, hypotheses are formed based on the historical performance of factors during the preceding crises. The objective is to analyze whether the relative performance of factors during the Covid-19 has been similar as in previous crises.

Sub-Question 1.1. *What elements explain the differences in performance?*

The second research objective is to analyze the elements that explain the difference in performance among factors. The methodologies of factor indices are analyzed and categorized to identify the main differences between factor indices. The contribution of sector performance to the total returns of factors is also analyzed. The relative valuation with analyst consensus estimates is conducted as well to perceive whether the performance of factors is explained by the estimated change in earnings or by the expansion of price-to-earnings multiple[2].

[2] The expansion of the price-to-earnings multiple indicates a rise in P/E multiple.

Sub-Question 1.2. *How correlated the returns of factors were ex-ante and midst the Covid-19 crisis?*

The third research objective is to analyze the correlation of factors ex-ante and midst the Covid-19 crisis. The correlations are compared to perceive whether the factors offer any diversification benefits and how the correlations change during the Covid-19 crisis. In addition, the elements that explain the correlations between factors are analyzed.

Question 2. *How the pure factor portfolios performed during the Covid-19?*

The fourth research objective is to analyze the performance of constructed pure factor portfolios. The methodology of pure factor portfolios is based on the best practices from academia and is inherently more transparent. Pure factor portfolios are constructed by applying both equally- and market-weighted methodologies as well as long-only and long-short strategies to achieve extensive results. The achieved results are compared to the results of factor indices, and the elements that explain the performance are analyzed. The objective is to achieve a more pure performance of factors.

1.3 Limitations of the research

In this sub-section, the major limitations concerning the time-period, asset class, indices, and factors are presented. It is essential to set limitations for the research to manage the scope of the study (Simon 2011). According to the evaluation by Harvey, Liu, and Zhu (2016), there are at least 300 different factors published, but even thousands of factors might have been tested. This research is carried out with five factors, which are value, size, momentum, quality, and ESG, to control the scope of the study. These factors, except the ESG, were selected for the study since these factors have a strong academic base, and therefore, the results of this study can be compared to previous findings. The ESG factor is a relatively new factor, and it is included in the study since environmental, social, and governmental aspects are becoming an increasingly important part of an investment process.

This study focuses solely on publicly listed equities, but factor investing can be utilized in several different asset classes, for example, in fixed income, currencies, and commodities (see, e.g., Asness et al. 2013). The studied factor indices are limited to four indices for each factor and are selected according to the assets under management of ETFs following the indices.

The geographical universe in this study is limited to the United States and Europe. The S&P 500 index is used as the benchmark index for U.S. factors, whereas Stoxx 600 is used for European factors. The sample period is limited from the beginning of January until the end of June 2020. This time period has been chosen since it contains both the bear market and the recovery market during the Covid-19 pandemic. The Covid-19 is still ongoing, however, this study covers approximately the first six months of this pandemic in 2020. The stock market in developed markets did not fully price the impact of Covid-19 until the end of February 2020 (Bloomberg Terminal 2020). The gross total return data is applied for both indices and ETFs, and thus the taxes of dividends are excluded from the returns. The total costs of ETFs will be taken into account when analyzing the performance.

1.4 Structure of the research

Section one, the introduction, gives an overview of the research subject. *Section two* presents the literature review and previous academic findings related to the subject of the research. *Section three* describes the data and methodology in detail. *Section four* presents the empirical results, while *section five* concludes with suggestions for further research.

I wish you a very enjoyable reading experience with this research.

2. LITERATURE REVIEW AND PREVIOUS FINDINGS

Figure 4 illustrates the theoretical framework of this thesis. The efficient market hypothesis was developed in 1970 by Eugene Fama. However, before the efficient market theory, the market inefficiencies were already recognized, for example, by Graham and Dodd (1934), who wrote the book named *"security analysis".* Factor investing has challenged EMH by recognizing persistent drivers of stock's long-term returns (Goltz and Luyten 2019). Fama and French's (1993) study regarding the three-factor-model is one of the most quoted studies related to factor investing. After Fama and French's publication, the number of studies related to factor investing started to pick-up. According to Harvey et al. (2016), there are exponential growth related to factor research and even hundreds of published papers related to different factors. In practice, the factor investing with ETFs became possible in the early 2000s when the first factor ETF emerged. Now there are an abundant amount of literature and investment instruments focusing on factor investing.

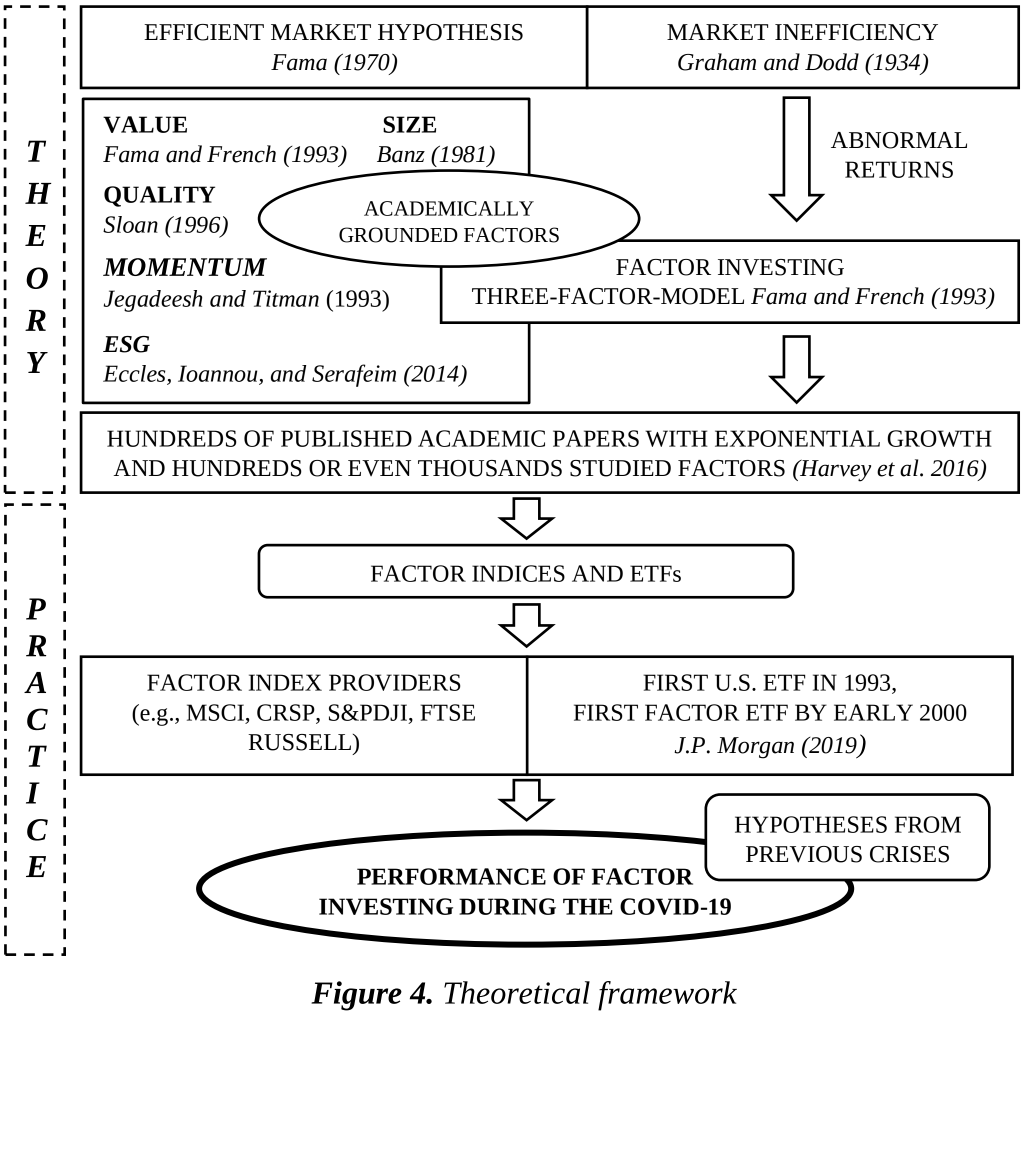

Figure 4. *Theoretical framework*

Crises occur irregularly, and thus every new crisis offers the possibility to study the performance of different factors during unordinary market environments. The contribution of this study is to advance the academic debate related to the performance of studied factors during the time of crises. In the field of factor investing, the studies are often focusing on finding new factors or studying the performance of factors in different markets or time periods. There is a relatively low number of studies related to the performance of factors during crises, and no studies related to the performance of academically grounded factors during the Covid-19.

2.1 Brief history of factor investing

The initial foundation of factor investing can be traced back to the '30s when Benjamin Graham and David Dodd (1934) published their book, "*Security Analysis*". Later Graham (1949) published the book "*The Intelligent Investor*", which can be considered as a bible of value investing. In their books, Graham and Dodd (1934; 1949) did not explicitly mention value stocks or factor investing, but they presented the characteristics of stocks that tend to outperform markets in longer time periods. As of now, this investment style is known as value investing, and it was later popularized by Warren Buffett (Buffett 1984).

The academic roots of factor investing reaches to the 1960s when the Capital Asset Pricing Model was developed by Treynor (1961, 1962), Sharpe (1964), Lintner (1965a, b), and Mossin (1966). The CAPM identified beta as a factor for explaining expected stock returns. The CAPM is inspired and based on Markowitz's (1952) modern portfolio theory, and according to the CAPM, investors can get higher returns by increasing the level of risk taken. The equation of CAPM can be seen below (Equation 1). The expected return ($E(r_i)$) of an investment is dependent on the risk-free rate (R_f), the beta of an investment (β_i), which is the sensitivity of investment return relative to the market return, and the market risk premium ($E(R_m) - R_f$), which is the difference between market return and risk-free return. (Mullins 1982) Essentially, all factor models are in some manner based on the initial CAP-model, although the number of different factors has increased in later models.

$$E(r_i) = R_f + \beta_i(E(R_m) - R_f) \quad \textbf{(1)}$$

Later in the '70s, after the foundation of the CAPM, Ross (1976) introduced the Arbitrage Pricing Theory, where he argued that multiple macroeconomic factors explain the returns of stocks. Ross (1976) recognized that several different factors can explain the returns, and consequently, APT can be viewed as a multi-factor model in contrast to the single-factor valuation model (CAPM). In addition to this, Ross (1976) can be considered as the founder of the term *"factor"* in this context since the APT-model was called a *"multi-factor model"*.

A relatively large amount of academic research on factor investing began to emerge after the foundation of the CAPM and APT. For example, Banz (1981) studied the *"size effect,"* and the results showed that smaller companies had better risk-adjusted returns compared to larger companies over the 40-year time period. According to Jegadeesh and Titman (1993), abnormal positive returns can be achieved during 3 to 12 months' time periods by investing stocks that have performed well in the past since the market often overreacts to new information. Jegadeesh and Titman (1993) did not explicitly mention the momentum strategy but described the basic principles of it. However, according to their study, part of the excess returns generated during the first 12 months dissipates in the following two years. Lakonishok et al. (1994) studied the value strategies, and they provided evidence that value investing generates higher returns compared to *"glamour strategies"*, as stated in the study referring to growth strategy as it is known nowadays. Sloan (1996) conducted a study regarding the earnings quality. The study showed that the persistence of earnings performance is dependent on the magnitudes of the earnings cash flows and accrual elements. Based on his findings, a portfolio that goes long on companies reporting low levels of accruals compared to cash flows and vice versa goes short on companies reporting high levels of accruals should produce abnormal positive returns.

Over the decades, there has been a lot of research based on factor investing. Nevertheless, Eugene Fama and Kenneth French (1993) can be considered as pioneers of factor investing in academic literature. Fama and French (1993) published their paper called *"Common risk factors in the returns on stocks and bonds"* in 1993, where they advanced the CAPM and argued that value stocks tend to outperform growth stocks and small companies outperform big companies. Fama and French (1993) also represented the market factor, which is the equity risk premium or the excess return of investing in stocks compared to the risk-free rate as presented in the CAPM. Carhart (1997) advanced this model known as the three-factor model to a four-factor model where the momentum factor was taken into account. Later in 2015, Fama and French (2015) enhanced their three-factor model and added two more factors, which are investment patterns and profitability. According to the five-factor model by Fama and French (2015), high operating profitability implicates higher stock returns, whereas conservatively investing companies should have higher expected returns compared to aggressively investing companies.

Factor investing emerged from the academy and is now a widely practiced investment strategy. According to Harvey et al. (2016), there are hundreds of different factors identified and published by academia. Cochrane (2011) even refers to this time as a *"zoo of new factors"*. Factor investing has never been as popular as it is nowadays (Goltz and Luyten 2019). Goltz and Luyten (2019) highlighted how factor investing and new factors are becoming removed from academically-grounded research, which can lead to unintended exposures and spurious factor definitions. Goltz and Luyten (2019) even compare the investments to provider-specific factor definitions to the risk of selecting an active manager.

2.2 Academic contributions for and against factor investing

The efficient market hypothesis is one of the most debated subjects in the field of finance. There is conflicting debate about whether the historical excess returns of factor investing are for or against the efficient market hypothesis. According to the efficient market hypothesis, stock prices already reflect all the available information and trade at their fair prices. Simply put, a constant generation of excess returns or market timing should not be possible. However, an efficient market hypothesis acknowledges that higher returns can be obtained by taking a higher risk. In premise, factor premiums can be reflected as systematic abnormalities from the efficient market hypothesis. The advocates of EMH argue that factors are inherently riskier and therefore are not conflicting evidence against EMH. (Fama 1970; Russel and Torbey 2002; Bender et al. 2013; Naseer and Bin Tariq 2015; Koedijk, Slager, and Stork 2016)

Ang (2014, 444) states that factor investing is an investment strategy that generates high returns over long time periods by targeting risk premiums. However, Ang (2014) acknowledges that factors can underperform in the short run, especially during bad times, and it is not a free lunch on the market. Goltz and Luyten (2019) support this view and add that factor investing is an investment strategy to identify persistent long-term drivers of return in a portfolio. Goltz and Luyten (2019) argue that investors should rely only on traditional factors that have survived the scrutiny of numerous academic studies and have been validated independently. According to the results of Chow, Hsu, Kalesnik, and Little (2011), the added value of new factors can be credited entirely to the exposures of existing factor premiums. Bender et al. (2013) advocate the tilts towards standard factors that have been historically earned excess returns over the market capitalization-weighted indexes. Blitz (2016) presented that equally-weighted factor portfolios are shown to result in better returns compared to market value-weighted factor portfolios.

Various academic studies have highlighted the long-term excess return of factor investing, pioneers and often quoted studies within the field include Banz (1981), Fama and French (1993; 2015), Jegadeesh and Titman (1993), Lakonishok et al. (1994), and Sloan (1996). However, there is literature against the performance of factor investing as well, especially when the practical aspects are considered. Malkiel (2014) argues that the track record of factor ETFs is quite spotty on a general level, especially when the survivorship bias is considered, and only a few ETFs have been able to earn excess returns relative to the market over the life of the fund. Therefore, Malkiel (2014) argues that smart beta portfolios can be considered as a marketing gimmick. Malkiel (2014) also remarks that historical performance is no guarantee of future performance. Jacobs and Levy's (2014) findings are consistent with Malkiel’s (2014) study. Jacobs and Levy (2014) referred that there is not much supporting evidence that the simple factor-based approach can consistently and easily generate excess returns.

Arnott, Harvey, Kalesnik, and Linnainmaa (2019) emphasized that factor investing can lead to poor returns for multiple reasons. Many essential practical issues are ignored and unstudied in the academic papers, which can lead to exaggerated expectations related to the performance of the factors. First, academic research often does not take into account many real-life issues, e.g., the trading or management fees that are incurred when investing in factors, and thus distorts the results from a real-life perspective. Second, investors often have a naïve illusion of the distribution related to the returns of factor strategies since often the factor returns stray far from a normal distribution. Third, Arnott et al. (2019) emphasize that investors often have the illusion that investing in more than one factor eliminates unsystematic risk altogether. Arnott et al. (2019) also remark that factor premiums can disappear when the factors became crowded. Regarding this, McLean and Pontiff (2016) and Arnott, Beck, and Kalesnik (2016) demonstrated how the performance of factors deteriorates after the publication. This is consistent with Lo's (2004) adaptive market hypothesis, which postulates that academically documented factors for explaining stock returns might lose their explanatory power after the public dissemination of the factors. Harvey and Liu (2015) argued that some tested factors will look good in the backtest, which is only a consequence of overfitting and data mining. Blitz (2016) analyzed different factor strategies and noticed that factor strategies typically tend to target one factor at a time, but the amount of exposure can vary between factors. Many factors do not offer maximum tilt to the targeted factor and instead contains a significant market exposure or even unexpected exposure to untargeted factors (Blitz 2016).

Factor investing is also studied in the context of sector investing. The objective of sector investing is to identify and allocate exposure to specific segments of the economy to manage risk, diversify, and achieve growth (Fidelity 2020). Brière and Szafarz (2017a; 2018) studied factor investing by utilizing sector investing as the benchmark. The results of Brière and Szafarz (2017a; 2018) showed that factor investing produced superior returns compared to sector investing, especially if short-selling of stocks was allowed. According to Brière and Szafarz (2017a; 2018), sector investing is more attractive during crises and bear markets, whereas factor investing tends to be more profitable and can push up the returns during normal market environments and bull markets. Brière and Szafarz (2017a; 2018) argued that higher returns with better diversification can be obtained by combining sectors and factors.

2.2.1 Long-only and long-short strategies

Factor investing can be implemented by taking long-only or long-short positions. In a long-only position investor generally buys and owns the stocks that have the highest desired factor tilt. In a short position, the investor first borrows the stocks from other investors and then sells this position with an intention to buy-back the position at a lower price. Finally, the investor should settle the position by returning the borrowed stocks to the original owner. In a long-short position, the investor aims to go short on stocks that have the least amount of factor tilt and go long on stocks that have the highest factor tilt. Therefore, the investor is long on stocks that are anticipated to appreciate and short-sell stocks that are anticipated to depreciate. (Jacobs and Levy 1997; Jacobs, Levy, and Starer 1999; Ang 2014, 444-445)

There are contradictory results related to the performance of long-only and long-short strategies. Israel and Moskowitz (2013) studied the role of shorting and its effects on the performance among size, value, and momentum factors. The results of Israel and Moskowitz (2013) showed that the long-only approach accounts for almost all of the returns regarding the size factor, 60% of the value factor, and half of the momentum factor. According to Brière and Szafarz's (2017b) study, short positions can greatly enhance the performance of factor investing. They also argued that long-short strategies can show very attractive mean-variance performance.

Ilmanen and Kizer (2012) and Blitz (2016) argued that theoretically, the benefits of factor investing are greater through long-short positions since it captures the pure premiums instead of asset premiums and has a lower correlation among asset class premiums compared to long-only portfolios. This is also in line with Blitz, Huij, Lansdorp, and Van Vliet's (2014) study, where they argued that the long-short strategy is theoretically superior in the context of returns. However, Blitz et al. (2014) argued that the long-only strategy has shown to be more preferable in most scenarios after taking account of practical issues such as implementation costs, benchmark restrictions, and factor decay. Blitz et al. (2014) even found evidence that in some scenarios, after taking account of the costs and decay, the value-added disappears completely from the long-short positions. These results were in line with Cazalet and Roncalli (2014) and Blitz (2016), who noted that in practice, factor investing is usually implemented by using a long-only approach. Novy-Marx and Velikov (2016) studied the effect of transaction costs in factor investing. Their results showed that almost none of the constructed long-short factor portfolios with a turnover surpassing 50% were able to show any excess returns after taking into account the impact of transaction costs. In addition, Jacobs et al. (1999) pointed out that the long-short approach is often portrayed as essentially riskier and costlier relative to a long-only approach. This is due to the concern related to the potentially unlimited losses that can result from the short positions, and if leverage is applied, this can extend the risks even further.

According to Blitz (2016), in academia, factor portfolios are typically constructed by using the methodology defined by Fama and French (1993), in which 30% of the least attractive stocks are shorted and going long in the 30% of the most attractive stocks within the same factor. Blitz (2012) presented an alternative method that considers a long-only approach where 30% of the most attractive stocks are going long. In addition, only large market capitalization stocks are eligible to be included in the portfolio. Blitz (2012) proposed this methodology since it should be easier to implement in practice, especially because short-selling or investing in illiquid stocks are not burdening the investment process.

There are a lot of studies that advocate the long-short strategy over a long-only approach (e.g., Brière and Szafarz 2017b), whereas some studies prefer a long-only strategy (e.g., Blitz 2012). However, many studies have shown that while the long-short strategy might work better in theory, the long-only strategy might work better in practice. This is also supported by the fact that today's investment products, such as factor ETFs that provide investors exposure to factor premiums, are mainly long-only.

2.2.2 Correlation

The correlation and diversification benefits of factor investing have been studied in academia, and the results are ambiguous. Bender, Briand, Nielsen, and Stefek (2010), Page and Taborsky (2011), and Ilmanen and Kizer (2012) argued that in general and particularly during the market crashes, factor-based diversification has been more attractive compared to traditional asset-class diversification. Cakici, Fabozzi, and Tan (2013) and Asness et al. (2013) found a negative correlation between value and momentum long-short factor portfolios across different market areas. Asness, Frazzini, Israel, Moskowitz, and Pedersen

(2018) proved a strong negative correlation between size and quality long-short factor portfolios. Clarke, De Silva, and Thorley (2016) studied correlation among factors (market, low beta, small, value, and momentum) by using annualized factor returns in the US equity market over the period of 1968-2015. The correlations among studied factors were negative or very close to zero. In addition, Melas, Nagy, and Kulkarni (2016) provided evidence that the correlations between ESG and traditional risk factors such as value, size, quality, and momentum were negative or very near zero during the period of 2007-2016.

On the contrary, according to Centineo and Centineo (2017), the correlations among factors (value, size, quality, momentum, and low volatility) were lower during the bear market compared to the longer time period. They used monthly returns from the 31st of December 1998 to the 30th of November 2015. The least correlated factors were low volatility and momentum (0.77 during the whole time period and 0.7 during the bear market) as well as momentum and value (0.81 during the whole time period and 0.77 during the bear market). Nevertheless, the correlations were relatively high overall. Brière and Szafarz (2017a) studied factor correlations by utilizing the U.S. monthly total return data from 1963 through 2014. The average recorded correlation between factors (small, big, value, growth, robust profitability, weak profitability, conservative investment, aggressive investment, high momentum, low momentum, and market) was 0.92. As can be observed, the evidence related to the correlation and diversification benefits of factors is contradictory. According to Ilmanen and Kizer (2012), diversification benefits are more effective when shorting is allowed, however, they noted that diversification is also beneficial in the context of long-only portfolios.

2.3 Studied factors

Table 1 exhibits significant academic literature and a basic description of the studied factors value, size, momentum, ESG, quality as well as the market factor. In the next sub-section, a literature review is conducted for each factor separately. In addition, hypotheses are formed for the studied factors regarding their performance during the Covid-19 based on the factors historical performance in preceding crises.

Table 1. *Studied factors including the market factor*

Factor	Literature	Description
Market	Treynor (1961; 1962); Sharpe (1964); Lintner (1965a, b); Mossin (1966)	The market risk premium is the difference in returns between the expected return of the risk-free rate and a market portfolio. The market risk premium can be calculated from the historical excess return of a market portfolio.
Value	Graham and Dodd (1934); Fama and French (1993); Lakonishok et al. (1994)	High book-to-market (value) firms should outperform low book-to-market (growth) firms. Other multiples often used to measure value vs growth firms include earnings-to-price, free cash flow to price, and dividend yield percentage.
Size	Banz (1981); Fama and French (1993)	Small-cap stocks should outperform large-cap stocks in the longer time period. Measured by firm's market capitalization.
Momentum	Levy (1967); Carhart (1997); Jegadeesh and Titman (1993)	High momentum stocks should outperform low momentum stocks and exhibit strong performance in the future as well. Analysts' revisions and recent historical performance are often used as a measure of the momentum.
ESG	Eccles et al. (2014); Nagy, Kassam, and Lee (2016)	Companies scoring high on Environmental, Social, and Governance (ESG) criteria should outperform companies with low ESG scores. Measured by using ESG criteria.
Quality	Sloan (1996); Novy-Marx (2013); Asness et al. (2019)	High quality stocks should outperform low quality stocks. Low debt to equity ratio, high return on equity, and stable earnings variability are often seen as quality characteristics.

2.3.1 Value factor

Lakonishok et al. (1994) define value strategies as a tendency of buying fundamentally undervalued stocks. They argue that value stocks tend to have a low price relative to book assets, earnings, dividends, or other indicators of fundamental value. Lakonishok et al. (1994) present that value strategies outperform *"glamour"* (formerly known as growth) strategies and the market index in the U.S. during the studied period of 1963 – 1990. Lakonishok et al. (1994) argue that value strategies are not fundamentally riskier but have higher returns because this strategy exploits the mistakes of common investors. They argued that the outperformance of value strategies is due to the reason that market participants may overestimate future growth rates of glamour stocks compared to value stocks, respectively. Damodaran (2020) argues that there are different forms of value investing, in which the most simplistic and most used is multiple based definition. The multiple based definition is the one that academia and many data service providers continue to utilize since it is convenient and quantifiable. Damodaran (2020) presents the term *"cerebral value investing"*, where in addition to multiples, other qualitative criteria are applied as well comprising the company's competitive advantage, economic moats, and quality of management.

There is an ample amount of literature that proves the existence of value premium in different markets over the past decades (see, e.g., Fama and French 1993; Dimson, Nagel, and Quigley 2003; Chan and Lakonishok 2004; Fama and French 2006; Cakici et al. 2013; Asness et al. 2013). The study performed by Nicholson (1968) was among the first to exploit the value effect. Nicholson (1968) found a notable difference in total returns regarding the high and low price-to-earnings (P/E) portfolios and argued that stocks with low P/E ratios provide consistently higher returns than stocks with a high P/E ratio. Nicholson's (1968) study concluded that stocks with price-to-earnings ratios over 20 had appreciated 32% on average during the studied five-year intervals from 1937 to 1962. Stocks with a price-to-earnings ratio of 10 times or less have appreciated 90% during the same period. Later in 1977, Basu (1977) obtained similar results for the value factor. He (1977) argued that portfolios with low P/E ratios outperformed the portfolios with high P/E ratios on average both in absolute and relative terms. Basu (1977) studied the P/E anomaly in the U.S. stock market during the time period of 1957-1971.

Fama and French (1998) studied the performance of value investing globally during the period 1975 through 1995. The results showed that the difference between a global portfolio of the highest and lowest book-to-market portfolios was 7.68% annually, and the results were statistically significant as well (t=3.45). In addition, Fama and French (1998) showed that value stocks with high book-to-market outperformed growth stocks and the market portfolio in twelve out of thirteen major market areas (except in Italy). Value premiums were also captured when the stocks were sorted by using earnings/price ratios, cash flow/price, and dividend/price ratios. The results were analogous with Piotroski (2000), who studied the value effect from 1976 to 1996. According to his results, annual returns can increase at least 7.5% on average by selecting financially strong companies with high book-to-market ratios.

There is contradictory evidence related to the reasoning for the outperformance of value strategies. Fama and French (1993) suggested that value strategies are fundamentally riskier and thus produce higher returns. Lakonishok et al. (1994) suggest that value strategies exploit the mistakes of the common investors and thus produce higher returns. Zhang (2005) and Winkelmann, Suryanarayanan, Hentschel, and Varga (2013) suggest that value stocks are less flexible to withstand economic downturns and shocks, and thus they are inherently riskier, especially in bad times when the price of risk is high. This observation is supported by the findings of Campbell, Giglio, and Polk (2013), which confirmed that value stocks perform better on average but worse during the downturns relative to the market, on average.

Chen and Zhang (1998) argued that value stocks are usually riskier since the companies are often under financial distress due to the higher leverage and greater uncertainty of future earnings. These findings are confirmed by Ang’s (2014, 230) study, where he highlighted the poor performance of value stocks during the recession in the early 1990s, and the tech boom of the late 1990s, as well as the financial crisis 2007-2008. Parallel results were also obtained by Lee, Strong, and Zhu (2014), who studied the value effect during the financial crisis in 2008, as well as by Yamani and Swanson (2014), who studied the value strategy globally during various financial crises. These studies advocate that value stocks are riskier compared to growth stocks due to poor performance during market shocks. However, Hsu (2014) stated that after the financial crisis value outperformed growth stocks by 44.4% cumulatively in the following 3 years. Arshanapalli and Nelson's (2007) findings suggest that value stocks tend to outperform growth stocks during non-recessionary periods and in bear markets but not in strong bull markets. Pätäri, Karell, and Luukka (2016) found evidence that value portfolios lose far less of their value than the market portfolio during the bear market periods. The parallel results have been obtained by Lakonishok et al. (1994), Bird and Whitaker (2003), Pätäri, Leivo, and Honkapuro (2010), and Hwang and Rubesam (2013). This is an interesting finding since this suggests that value stocks can act as a hedge under poor economic conditions. This finding is, however, contradictory to other reviewed literature.

The value effect has been very strong overall in the 20th century, according to the reviewed literature. However, more recent studies that study the post-1991 value premiums do not find a significant value premium, and even in some studies, the value premium is negative (Schwert 2003, 939-972; Wellington 2016; Linnainmaa and Roberts 2018). Fama and

French (2020) studied the value premiums during 56 years period from 1963 to 2019. They divided the period into two subperiods, the first time-period ending in 1991 and the second starting from the same year. The average value premium for the second half of the sample was much lower, high B/M compared to low B/M yielded only a 0.05% premium per month, and the result was not statistically significant. Hsu (2014) studied the performance of the S&P 500 value index and Russell 1000 value index and showed that the S&P 500 value index underperformed against the market index (S&P 500 index) in all studied time periods (3, 5, 10, 20, and 30 years). Russell 1000 value index underperformed the Russell 1000 market index in 3, 5, and 10 years but outperformed during the 20- and 30-year time periods.

According to Meredith (2019), value strategy has underperformed since the beginning of 2007. He studied value investing, measured by P/E and P/B ratios, and found a historical period between 1926 and 1941 when value investing underperformed as well. Meredith (2019) offered a theory that both of these periods coincide with the central turning point of technological revolutions. In the former time period, the fourth industrial revolution, oil, mass production, and automobiles boomed, whereas utilities and railroads from the third revolution declined. This is similar to the current time where information technology is flourishing and financials are declining amidst the regulation followed by the financial crisis.

As a conclusion and hypothesis, there is evidence of an excess return of value stocks over very long time periods. However, especially during the recent decade, value stocks have not been able to produce any reasonable excess returns. The explanation for this could be the adaptive market theory. However, a closer look revealed that there has been a similar time in history where value premiums did not exist due to the industrial revolution. Various studies concluded that value stocks are inherently riskier and value premiums are a reward for investing in stocks that are often under financial distress. This might imply that value stocks should underperform relative to the market during crises, including Covid-19 as well, albeit there were contradictory research findings in this regard.

Hypothesis: The value factor should underperform the market index during the Covid-19. *(Chen and Zhang 1998; Zhang 2005; Winkelmann et al. 2013; Campbell et al. 2013; Ang 2014, 230; Lee et al. 2014; Yamani and Swanson 2014)*

2.3.2 Size factor

The size factor refers to a tendency of small companies to outperform large companies measured by market capitalization (see, e.g., Banz 1981; Fama and French 1993; Reinganum 1981; Keim 1983; Bauman, Conover, and Miller 1998; Rizova 2006). Banz's (1981) study was among the first studies to examine the size effect in the U.S. markets from 1936 to 1975. He argued that the first quintile portfolio, including stocks with the smallest market capitalization, produced a better risk-adjusted return of 0.4 percent per month relative to the remaining counterparts. Banz (1981) concluded that the CAPM is misspecified due to this contradiction. The study conducted by Reinganum (1981) supports the findings of Banz (1981). Reinganum (1981) studied the U.S. markets with a sample size of 566 companies and showed that the smallest size decile outperformed the largest decile by 1.77 percent monthly during the studied period of 1963 – 1977. In addition, Reinganum (1983) added that even when the risk-adjusted-performance is taken into account, by applying beta, small-cap stocks tend to outperform large-cap stocks on average.

Keim (1983) studied the size effect in the U.S. market between 1963 and 1979. He argued that the size premium was 2.5% monthly even when the return is adjusted by the higher beta of small companies relative to their counterparts, the difference in returns is not fully explained. The excess return occurred especially in January and in the first trading week. Lamoureux and Sanger (1989) reported the average monthly size premium of 2.0% for Nasdaq stocks, whereas the premium was 1.7% for NYSE and Amex stocks from 1973 through 1985. Conversely, their findings showed that stocks with small market capitalization tend to have a lower beta compared to stocks with large market capitalization on Nasdaq. Annaert, Crombez, Spinel, and Van Holle (2002) studied the size effect for a cross-section of European companies. They found evidence that the size premium during the period of 1974 – 2000 was 1.45% on a monthly basis, on average. Annaert et al. (2002) argued that the size premium is relatively high and statistically significant if the stocks are chosen on a European basis neither on a country-by-country basis.

There has been an abundant amount of debate about what explains the size premium. According to Fama and French (1993), the size premium is explained by higher systematic risk concerning the small-cap stocks. Other studies have suggested that the size premium may be due to the underlying risk factors such as financial distress (Chan and Chen 1991), illiquidity (Amihud 2002), default risk (Vassalou and Xing 2004), and information uncertainty (Zhang 2006), associated with small market capitalization companies. An optional explanation for the size effect is that it is compensation for trading costs. On the other hand, some papers claim that the size effect is no more than a statistical fluke. (Van Dijk 2011) Winkelmann et al. (2013) stated that small-cap portfolios are more sensitive to economic shocks relative to large-cap portfolios, which implicate a higher risk and return concerning the small-cap companies. These findings are confirmed by Kilbert and Subramanian's (2010) study, where they presented that small-cap stocks performed poorly, as well as underperformed large-cap stocks during the financial crisis of 2007-2008. However, they pointed out that after the crisis, small-cap stocks rebounded faster.

Arshanapalli and Nelson (2007) mentioned that while small-cap stocks outperform on average, investors should be prepared to accept weaker performance during market crashes. Arshanapalli and Nelson (2007) also conclude that albeit the small-cap stocks suffer larger losses during the bear markets, the performance of small-cap stocks is very strong during the bull markets. The small-cap premium thus rewards investors for taking a higher risk. Switzer (2010) studied the performance of the size factor during economic peaks and downturns. According to the results, small-cap firms tend to outperform large-cap firms over the following year after the economic trough, whereas the year preceding business cycle peaks, large stocks tend to outperform small market capitalization stocks. The sensitivity of small-capitalization stocks to the market cycles is in line with the findings of Kilbert and Subramanian (2010) and Winkelmann et al. (2013).

In academia, there has been a lot of questioning whether the size premium still exists. Ang (2014, 228) argued that since the mid-1980s, there has not been any substantial size premium. This is confirmed by Horowitz, Loughran, and Savin's (2000) study, where they presented their findings regarding the existence of size premium in the U.S. over the period of 1963-1997. Their results proved the existence of size premium during the years 1963-1981 with an annual outperformance of over 13%. Nevertheless, they pointed out that the size premium has been very unsatisfactory during the years 1982-1997, as the small-cap decile yielded on average 1.30% per month, whereas the large-cap decile yielded 1.46%, respectively. As a result, Horowitz et al. (2000) argued that the size premium is not robust. Fama and French (2012) also confirmed that there was no size premium in North America, Europe, Japan, or the Asia Pacific during the sample period of 1989-2011. On the contrary to the previous studies, Asness et al. (2018) defend the existence of size premium and argue that when the quality of the small-cap stocks is controlled, a significant size premium still emerges that is resilient across time.

As a conclusion and hypothesis, there is evidence of an excess return of small-cap stocks over very long time periods. However, there is less evidence of small-cap anomaly during the recent time period. According to academia, small-capitalization stocks have a higher systematic risk due to higher financial distress, illiquidity, default risk, and information uncertainty, thereby making this factor more sensitive to withstand economic downturns. The size factor is expected to underperform relative to the market during the beginning of the Covid-19 crisis but recover more promptly at the recovery phase.

Hypothesis: The size factor should underperform the market index during the bear market but rebound faster during the recovery period. *(Arshanapalli and Nelson 2007; Switzer 2010; Kilbert and Subramanian 2010; Winkelmann et al. 2013)*

2.3.3 Momentum factor

The price momentum refers to the tendency of stocks with strong recent performance (also known as winners) to maintain the upward trend in the short-term and outperform the markets, while the stocks with poor recent performance (also known as losers) tend to underperform the market, respectively. This momentum effect has been identified in numerous academic studies (see, e.g., Levy 1967; Jegadeesh and Titman 1993; Chan, Jegadeesh, and Lakonishok 1996; Carhart 1997; Rouwenhorst 1998; Chan, Hameed, and Tong 2000; Korajczyk and Sadka 2004; Gutierrez and Kelley 2008; Israel and Moskowitz 2013).

The momentum effect emerged in the academic literature with Levy (1967), but this factor was to some extent ignored until the Jegadeesh and Titman's (1993) study. Levy (1967) observed that investors can achieve superior returns by investing in securities that have a strong historical price movement. Jegadeesh and Titman (1993) found a significant momentum effect in the U.S. stock market between the period of 1965 through 1989. Jegadeesh and Titman (1993) formed portfolios by including the best-performing stocks during the past 3, 6, 9, and 12 months with equal holding periods. According to the results, the portfolio based on the stocks' past 12-month return with three months holding period produced the highest return from all of the momentum strategies.

Rouwenhorst (1998) studied the momentum effect internationally, including 12 European countries during the years 1980 to 1995. The main result was that the portfolio which buys past medium-term winners and sells past medium-term losers produced approximately 1% excess return per month after risk adjustment. Rouwenhorst (1998) argued that the portfolio's return continuation lasts approximately one year. Moskowitz and Grinblatt (1999) studied the momentum effect between various industries. They formed 20 different portfolios based on the industry-specific stocks and studied the efficiency of selling past losers and buying past winners by the industries. The results showed that all industries offered the momentum effect. However, according to Moskowitz and Grinblatt (1999), the momentum effect varies across industries. Thus, they extrapolated that industry-specific momentum is the explanation for the momentum effect of individual stocks. Fama and French (2012) found a robust momentum effect in North America, Europe, and the Asia Pacific during the period between 1989 through 2011.

There has been a lot of discussion about what causes the momentum effect. Jegadeesh and Titman (1993) argued that the momentum effect is not due to the systematic risk neither delayed price reaction. Instead, the overreaction and underreaction to new information by investors could explain the momentum effect, according to Jegadeesh and Titman (1993). They concluded that investors buy past winners and sell past losers affecting the prices to move away from their long-term averages temporarily, which causes the overreaction of prices. Jegadeesh and Titman (1993) add that another explanation could be that markets underreact to the news related to the short-term prospects of companies and overreact to the news related to the long-term prospects of companies. These findings are parallel with Barberis, Shleifer, and Vishny (1998), who pointed out that the momentum effect was explained by behavioral aspects such as overreaction and underreaction to the information by investors. Daniel, Hirshleifer, and Subrahmanyam (1998) pointed out two psychological biases about under- and overreactions, which are investor's overconfidence regarding the accuracy of private information and biased self-attribution.

Cheema and Nartea (2017) argued that the momentum strategy fails during a market crisis in every market but especially during the recovery period when the market conditions improve. An interesting observation was that during the financial crisis, the *"loser"* stocks outperformed the *"winner"* stocks from 2007 until 2010. The results were in line with Daniel and Moskowitz (2016), who confirmed that the momentum returns were the worst during the *"turning points"* of market crashes. Their results confirmed that after the financial crisis during the years 2009-2010, past "*winners*" underperformed relative to the market index. In addition, during the great depression in the 1930s, past winners underperformed both the market index as well as past "*losers*" stocks. According to Daniel and Moskowitz (2016), during the financial crisis after the U.S. stock market bottomed in March 2009, "*loser*" stocks outperformed "*winner*" stocks by 149%. Maheshwari and Dhankar (2017) studied the momentum strategy during the financial crisis in Indian markets by applying three different time periods that were pre-crisis period from 2005 to 2008, the crisis period from 2008 to 2009, and the post-crisis period from 2009 to 2013. During the pre-crisis period and post-crisis period, the momentum (long-only and long-short) portfolios generated higher risk-adjusted returns relative to the markets on average, but these returns were lower during the crisis period. The excess returns were statistically significant during the pre-crisis and post-crisis periods but not during the crisis period.

There are recent studies as well related to the performance of the momentum factor. Imran, Wong, and Ismail (2020) studied the existence and profitability of momentum strategies, including forty different countries globally between 1996 through 2018. Their findings proved that the significant momentum effect can be identified in 90% of the selected countries of which 52.5% produced positive momentum, whereas 37.5% produced negative momentum. The momentum strategy is not solely restricted to equity since it can be observed across different asset classes. Cheng, Liu, and Zhu (2019) identified that the momentum effect can be seen in the cryptocurrency market as well, and it was especially strong in

Ethereum and Bitcoin. On the contrary, Hwang and Rubesam (2015) argued that the momentum premium has slowly vanished since the early 1990s, although the momentum effect was extended by the information technology bubble in the late 1990s.

As a conclusion and hypothesis, the momentum effect should still exist, and it is a profitable investment strategy with a relatively strong academic background, however, contrary evidence exists. According to the literature review, momentum stocks tend to underperform markets during crises, especially during the crisis recovery phase.

Hypothesis: The momentum factor should underperform the market index during the Covid-19, especially during the recovery period. *(Daniel and Moskowitz 2016; Cheema and Nartea 2017; Maheshwari and Dhankar 2017)*

2.3.4 ESG factor

The ESG (Environmental, Social, and Governance) investing, also sometimes referred to by narrower terms Socially Responsible Investing (SRI) or Sustainable Investing, is becoming an increasingly important part of investment decision-making (MSCI 2020a). ESG as an investment style refers to a consideration of environmental, social, and governance criteria in the investment decision-making process. This relatively new and non-traditional factor has gained momentum in recent years, and the ESG criteria have become a matter that the corporations and institutional investors are increasingly taking into account in everyday operations. (Amundi 2020; MSCI 2020a) Along with the rise of responsible investing, there is an increasing number of academic studies related to the performance and returns of ESG-investing (see, e.g., Eccles et al. 2014; Nagy et al. 2016; Kumar, Smith, Badis, Wang, Ambrosy, and Tavares 2016; Verheyden, Eccles, and Feiner 2016; Pollard, Sherwood, Klobus 2018).

Eccles et al. (2014) studied 180 U.S. companies, in which 90 were classified as highly sustainable companies and the other 90 as low sustainable companies, respectively. Eccles et al.’s (2014) findings provided evidence that during the 18-year studied period, the companies with high sustainability significantly outperformed the low sustainability companies in terms of accounting measures as well as stock market performance. Eccles et al. (2014) added that outperformance occurs only in a longer time period. Nagy et al. (2016) studied ESG-investing through two different strategies by applying MSCI's ESG data. The first strategy was *"ESG tilt",* where stocks were weighted in the portfolio according to their ESG rates. The second strategy *"ESG momentum"* refers to the strategy, which overweight stocks in the portfolio that have been able to improve their ESG-rates over the recent time period. Both of these global portfolios outperformed the MSCI World market benchmark index. These findings were in line with the results of Kumar et al. (2016), who argued that ESG stocks in the same industry produce a higher return with lower volatility relative to the peers in the same industry. On the contrary, Auer and Schuhmacher (2016) argued that selecting high (low) ESG-stocks in the U.S. or Asia-Pacific does not generate consistently higher (lower) returns relative to the benchmark market indices nor low (high) ESG stocks. Auer and Schuhmacher (2016) also added that ESG-investing does not provide superior risk-adjusted returns in Europe either. They even argued that investors might end up with a lower risk-adjusted return when investing in ESG stocks and not in passive market indices.

Ghoul, Guedhami, Kwok, and Mishra (2011) argued that socially responsible companies have a higher valuation and lower cost of capital, which can explain the outperformance of such companies. This argumentation is consistent with Cheng, Ioannou, and Serafeim's (2014) study, where they argued that socially responsible companies face substantially lower capital constraints. Drempetic, Klein, and Zwergel (2019) raised an observation that there is a clear connection between the ESG-scores and firm size, denoting higher ESG scores to larger firms as larger firms have more resources to achieve social responsibility and provide ESG-data. Hvidkjær (2017) suggested that the outperformance of ESG-stocks is due to the fact that ESG companies are undervalued since the markets underreact to ESG information. The second reason Hvidkjær (2017) presented is that the outperformance might be due to the increasing popularity towards these strategies.

There is evidence related to the performance of responsible investing during the market crises and even a few studies during the Covid-19. Nofsinger and Varma (2014) argued that socially responsible funds tend to outperform conventional funds during market crises. These findings were in line with Lins, Servaes, and Tamayo's (2017) study, where they presented that socially responsible companies tended to outperform companies with low social responsibility by at least 4% after controlling risk factors and firm characteristics during the financial crisis on 2008-2009. However, they concluded that there is no difference in returns during the recovery period. Albuquerque, Koskinen, Yang, and Zhang (2020) studied the resiliency of ES (Environmental and Social) stocks during the Covid-19 market crash. They provided evidence from the U.S. stock market from the first quarter of 2020. The study showed that high ES rated stocks have produced considerably higher returns, lower volatilities, and higher operating profits compared to other stocks. They claimed that the performance of high ES stocks was especially robust during the bear market. The excess return for high ES rated stocks was on average 0.45% per day from the 24^{th} of February to the 17^{th} of March. Their study highlighted the significance of ES policies leading to better resilience during market crashes. The results during the Covid-19 were similar to Nofsinger and Varma's (2014) and Lins et al.'s (2017) findings from previous crises.

Pollard et al. (2018) came to the conclusion that ESG should be included alongside other academically-grounded factors since it provides geographically and longitudinally excess returns. Amundi's (2020) study highlights that the importance of ESG aspects in the investment decision process has become more significant during the Covid-19. In addition, Amundi's (2020) study notes that the environmental aspects, climate change, and global warming were the main focuses on ESG before the Covid-19. Amundi (2020) argues that after the Covid-19, the focus will shift more to the social pillar, especially on the health and safety of employees and employment practices when adopting ESG criteria.

As a conclusion and hypothesis, ESG aspects have increased in popularity, especially during the past recent years. According to the literature review, various studies identified that companies with a high ESG profile tend to have a lower risk and higher return. Especially during crisis and bear markets, companies with a high ESG rating should outperform the markets and companies with low ESG rating.

Hypothesis: The ESG factor should outperform the market index during the Covid-19, especially during the bear market. *(Nofsinger and Varma 2014; Lins et al. 2017; Albuquerque et al. 2020)*

2.3.5 *Quality factor*

The quality factor is often associated with the profitability of a firm, and according to the hypothesis, highly profitable firms should yield higher returns than less profitable firms, although having higher valuation multiples (Novy-Marx 2013). Kalesnik and Kose (2014) mark out that there is no clear or widely applied definition for quality investing, unlike for more established factors such as momentum and value. Kalesnik and Kose (2014) refer that along with profitability, which is often measured by using the gross profits to assets ratio, other financial ratios are adapted as well to identify quality companies. Kalesnik and Kose (2014) identified that the following financial ratios are applied to define quality characteristics of a firm: profitability, margins, leverage, financial constraints and distress, earnings stability, dividend payout, accounting quality, and growth activities. Bender et al. (2013) affirms the findings of Kalesnik and Kose (2014) and concludes that the quality factor is multidimensional without an unambiguous definition, and thus it can be recognized differently in different studies. The performance of quality factor investing has been reviewed in several academic studies (see e.g., Antunovich, Laster, and Mitnick 2000; Novy-Marx 2013; Gallagher, Gardner, Schmidt, and Walter 2014; Fama and French 2015; Asness et al. 2019).

Benjamin Graham is identified to be one of the first investors to publicly identify quality investing already in 1949. In his book *"The Intelligent Investor"* he argued that the greatest losses occur from buying low-quality firms at times of favorable business conditions, not from buying quality firms at a too high price. Asness et al. (2019) studied the performance of the quality stocks covering the United States and 23 other countries from the MSCI World Developed Index from 1957 to 2016. They concluded that high-quality stocks do exhibit higher returns on average, however, the explanatory power was relatively low. The results of Asness et al. (2019) revealed that the quality factor is outperforming, especially when the risk-adjusted returns are considered on long-short portfolios (quality-minus-junk). These results implicate that quality stocks are underpriced whilst junk stocks are overpriced. The results were affirmed by Antunovich et al. (2000) study, where they presented that high-quality companies generate higher returns than the stock markets on average. According to

Novy-Marx (2013), the returns can be increased even further by combining quality factor to other studied factors.

As has already been stated, the quality of companies is defined in different ways and various measurements can be utilized when determining the quality of a company. According to Novy-Marx (2013) and Fama and French (2015), companies with higher profitability tend to outperform their counterparts. George and Hwang (2010) concluded that companies with low leverage have higher excess returns relative to companies with high leverage. Similarly, Campbell, Hilscher, and Szilagyi (2008) remarked that companies with higher credit risk tend to underperform their counterparts. Mohanram (2005) argued that companies with high growth tend to outperform companies with low growth. Hou, Xue, Zhang (2015) showed that companies with higher return-on-equity (ROE) tend to outperform companies with low ROE on average, whereas companies with high accruals tend to underperform companies with low accruals (Sloan 1996). Berkshire Hathaway's risk-adjusted return (Sharpe ratio 0.79) is higher than any other stock or fund has achieved over a period of 40 years (Frazzini, Kabiller, and Pedersen 2018). According to Frazzini et al. (2018), the secret of Berkshire Hathaway's success is partly explained by the fact that the company aims to invest in stocks that are cheap, safe, and reflect high-quality characteristics.

Only a few explanations about the outperformance of quality stocks have been identified in the academic literature, which might be due to the ample amount of definitions concerning the quality factor. Antunovich et al. (2000) suggest that investors underreact to the presence of a firm's quality. Bouchaud, Ciliberti, Landier, Simon, and Thesmar (2016) provided two potential explanations for the quality anomaly. The first view is consistent with EMH by Fama (1970), where higher returns are compensation for taking a higher risk. The second view argues that quality stocks are undervalued since investors and analysts persistently underestimate the intrinsic value of high-quality stocks. However, Bouchaud et al. (2016) concluded that quality stocks are not riskier and suggest that analysts systemically underestimate the value of quality companies. Consistent with Bouchaud et al. (2016), Asness et al. (2019) identified that quality stocks are not riskier but rather the opposite. Quality stocks often have a lower beta and tend to perform well during severe market conditions (Asness et al. 2019). George (2002) achieved similar results during the IT-bubble.

According to his findings, quality stocks outperformed the S&P 500 index both in bull and bear market environments. Based on Asness et al. (2019) findings, it can be concluded that in the aftermath of each crisis (1987 crash, 2000 IT-bubble, and 2008 the great financial crisis) companies reflecting quality characteristics have performed very strongly.

As a conclusion and hypothesis, quality stocks should be less risky due to strong profitability and lower beta. Therefore, especially the risk-adjusted return should be higher relative to the market index. According to academia, low-risk/defensive companies (e.g., low leverage, low risk, low cyclicality, and high profitability) should outperform high-risk companies (high leverage, high risk, high cyclicality, and low profitability). A scarce amount of academic literature exists related to the performance of quality factor during the market crashes, therefore, no comprehensive hypothesis could be formed. However, according to the limited literature, historically, quality companies have outperformed during the time of crisis.

Hypothesis: The quality factor should outperform the market index during the Covid-19, especially during the bear market. *(George 2002; Asness et al. 2019)*

2.4 Covid-19

Coronavirus disease 2019 (Covid-19) is a global contagious disease caused by a SARS-CoV-2 virus (World Health Organization 2020a). The outbreak of this novel virus, according to the current knowledge, began in China's Wuhan in late 2019 when Wuhan Municipal Health Commission, in China, announced a cluster of pneumonia cases (World Health Organization 2020c). According to WHO (2020c), the first case outside of China was recorded in Thailand on the 13th of January 2020. After that, the virus began to spread all around the world, and on the 11th of March, WHO (2020c) announced that it is a global pandemic. Covid-19 is still an ongoing and evolving pandemic and there is no vaccine for Covid-19 at the time of writing. There have been approximately 42.5 million confirmed cases globally with more than 1.14 million fatalities until now (25.10.2020) (World Health Organization 2020b).

The countermeasures used to control the spread of Covid-19 restricted economic activity, which affected companies and the value of most stocks and indices tumbled down around the world (International Monetary Fund 2020; Bloomberg Terminal 2020). As an illustration of the market turmoil, an unprecedented happened, and the price of WTI (West Texas Intermediate) May delivery oil futures went into negative territory for the first time on the 20th of April 2020 (Bloomberg Terminal 2020; Tobben 2020).

Governments and central banks around the world stimulated the economy with a monetary and fiscal policy that supported the recovery from the Covid-19 (International Monetary Fund 2020). In Europe, the European Central Bank started an asset purchase program on the 18th of March 2020, with 750 billion euros (European Central Bank 2020). In the U.S., the Federal Reserve (Fed) committed to taking actions as well. Figure 5 presents the development of the Fed's balance sheet compared to the S&P 500 index during the period from 3.3.2020 to 29.6.2020. In addition, the figure illustrates major actions taken by the Fed to respond to the Covid-19 pandemic. As can be seen from Figure 5, the S&P 500 index started its recovery shortly after the Fed's balance sheet started to accumulate. Fed's balance sheet increased from 4 trillion to approximately 7 trillion only in a matter of 3 months. The correlation between the Fed's balance sheet and the development of the S&P 500 index is 0.8 (statistically significant p=0.00002) during the period applied in the figure.

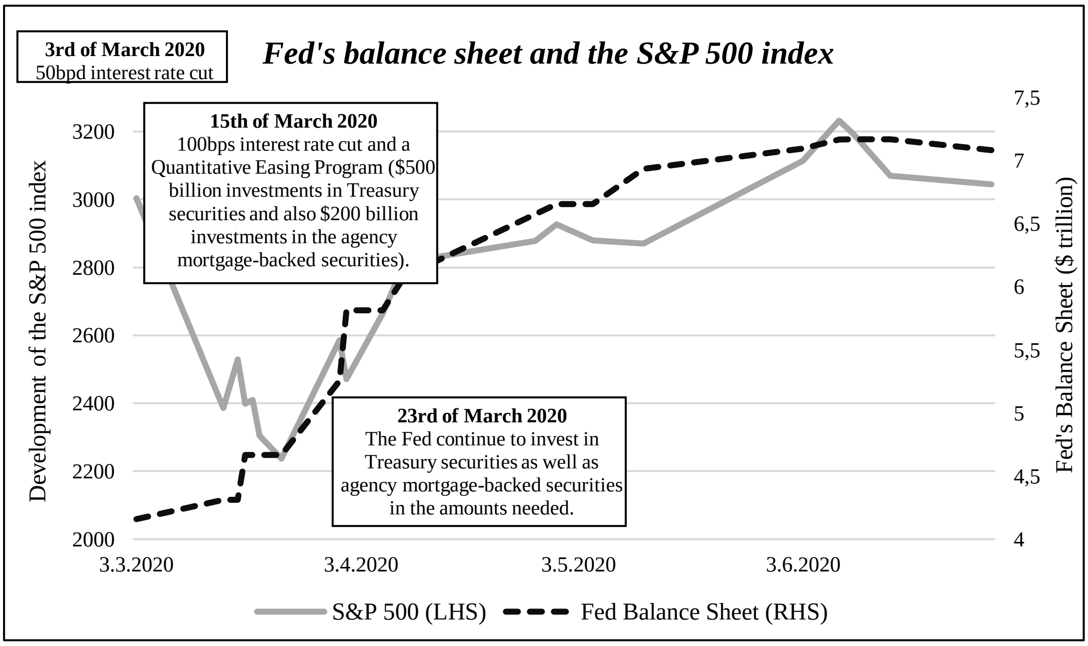

Figure 5. *The Federal Reserve's balance sheet and the S&P 500 Index (J.P. Morgan 2020; Federal Reserve Board 2020a; 2020b; 2020c)*

3. DATA AND METHODOLOGY

3.1 The data collection methodology

The data collection is a two-step process, where first the correct factor ETFs and indices for this study should be identified. The second step is gathering the daily gross total return price data for the selected ETFs and indices from the Bloomberg Terminal (2020). The data collection process is initiated by first defining the databases and data sources from which the correct ETFs and indices are searched. The information of factor ETFs is obtained from J.P. Morgan's (2019) global ETF handbook, ETFdb (2020), and FactSet (2020). Various criteria were applied to limit the number of results. First, equity was chosen as an asset class since this study focuses only on listed stocks. Developed markets were used as other criteria since the geographical focus is only on the U.S. and Europe. Keywords value, size, momentum, ESG, and quality were applied to achieve exposure only to the selected factors. These results were filtered and multi-factor ETFs (ETFs targeting two or more factors at the same time) were removed to obtain the performance of a single factor. In addition, industry-specific and country-specific factor ETFs, as well as active ETFs, were excluded. The final filtered results were sorted based on the amount of assets under management and ETFs with the largest AUM were chosen. A high AUM of an ETF typically indicates higher trading volume, which reduces the spread between the bid and the ask rates (Riepe and Iachini 2011). It can also be seen as an indication of the quality of the fund since more mature ETFs typically have a higher AUM and thus a longer track record. ETFs with high AUM can typically have a lower expense ratio and it can be interpreted that markets trust and prefer to invest in that ETF since the AUM is high. (Hill, Nadig, Hougan, and Fuhr 2015, 1-81)

The total search results are presented in Table 2. After data sorting, filtering, and factor categorization, there are a total of 147 factor ETFs in the U.S. and 21 in Europe that fulfilled the search criteria described above. Table 2 shows that value and size factors are the most common factors both in Europe as well as in the U.S., which may be explained partly by their strong academic background (e.g., Fama and French studies in 1993 and 2015). All search results of different factor ETFs including the name and AUM (2.7.2020) of ETFs are listed in Appendix 1.

Table 2. *The number of ETFs that fulfilled the search criteria*

Factor	Europe	USA
Value	8	38
Size	8	63
Momentum	1	9
ESG	3	32
Quality	1	5
Total	**21**	**147**

3.2 Description of the research data

The factor ETFs and indices were selected according to the AUM of ETFs. A total of 20 different ETFs and 20 factor indices were selected, four for each factor (value, size, momentum, ESG, and quality). According to data gathered from J.P. Morgan (2019), ETFdb (2020), and FactSet (2020), the U.S. factor ETFs have larger AUM compared to ETFs investing in the European area. Therefore, three ETFs from the U.S. market and one ETF from the European market were selected. The selected factor ETFs and their indices are presented in Table 3, in which the first three ETFs of each factor are investing in the U.S. markets and the fourth into the European markets. Table 3 (gathered 2.7.2020) also shows that the largest AUM is documented for the value factor category, *Vanguard Value ETF* (46.9 Bn$). By contrast, the largest AUM in the European markets is in the ESG factor category, *iShares MSCI Europe SRI UCITS ETF* (1.6 Bn€). The AUM of ETFs is denominated in the domestic currency of each market area.

Table 3. *The selected factor indices and ETFs*

Factor	Index	ETF Following/Ticker	AUM ($/€)
Value	1. CRSP US Large Cap Value Index	1. Vanguard Value ETF/VTV	46 900 000 000
	2. Russell 1000 Value Index	2. iShares Russell 1000 Value ETF/IWD	33 513 723 511
	3. S&P 500® Value Index	3. iShares S&P 500 Value ETF/IVE	15 212 646 078
	4. MSCI Europe Enhanced Value Index	4. iShares Edge MSCI Europe Value Factor UCITS ETF/IEVL	938 526 543
Size	1. S&P SmallCap 600® Index	1. iShares Core S&P Small-Cap ETF/IJR	39 625 824 228
	2. Russell 2000 Index	2. iShares Russell 2000 ETF/IWM	36 109 325 203

	3. CRSP US Small Cap Index	3. Vanguard Small-Cap ETF/VB	26 200 000 000
	4. MSCI EMU Small Cap Index	4. iShares MSCI EMU Small-Cap UCITS ETF/CEUS	639 522 316
Momentum	1. MSCI USA Momentum Index	1. iShares Edge MSCI USA Momentum Factor ETF/MTUM	9 587 664 437
	2. Dorsey Wright Technical Leaders Index	2. Invesco DWA Momentum ETF/PDP	1 724 600 000
	3. JP Morgan US Momentum Factor Index	3. JPMorgan U.S. Momentum Factor ETF/JMOM	112 650 000
	4. MSCI Europe Momentum Index	4. iShares Edge MSCI Europe Momentum Factor UCITS ETF/IEMO	238 026 717
ESG	1. MSCI USA Extended ESG Focus Index	1. iShares ESG Aware MSCI USA ETF/ESGU	6 898 759 240
	2. MSCI USA ESG Leaders Index	2. Xtrackers MSCI USA ESG Leaders Equity ETF/USSG	2 251 000 000
	3. MSCI USA Extended ESG Leaders Index	3. iShares ESG MSCI USA Leaders ETF/SUSL	2 255 954 574
	4. MSCI Europe SRI Select Reduced Fossil Fuel Index	4. iShares MSCI Europe SRI UCITS ETF/IESE	1 624 040 846
Quality	1. MSCI USA Sector Neutral Quality Index	1. iShares Edge MSCI USA Quality Factor ETF/QUAL	17 850 487 767
	2. S&P 500® Quality Index	2. Invesco S&P500 Quality ETF/SPHQ	1 938 000 000
	3. JP Morgan US Quality Factor Index	3. JPMorgan U.S. Quality Factor ETF/JQUA	329 830 000
	4. MSCI Europe Sector Neutral Quality Index	4. iShares Edge MSCI Europe Quality Factor UCITS ETF/IEQU	133 679 383

The market benchmark indices for studied factor indices are the S&P 500 in the U.S. and Stoxx 600 in Europe. The S&P 500 index incorporates 500 large-cap stocks from the United States, whereas Stoxx 600 incorporates 600 small, mid, and large-capitalization stocks from 17 different European countries (S&P Dow Jones Indices 2020a; Stoxx Qontigo 2020).

The performance of indices and ETFs is measured during the Covid-19 crisis in three different time periods to achieve a holistic view. The first time period is the bear market from the 20th of February 2020 to the 23rd of March 2020, whereas the second time period is the recovery market from the 24th of March 2020 to the 30th of June 2020. The third time period consists the full sample period from the 2nd of January 2020 to the 30th of June 2020. The study covers the first six months of the crisis in 2020 when the price volatility was high, albeit the stock market in developed markets did not fully price the impact of Covid-19 until the end of February 2020 (Bloomberg Terminal 2020). Due to the price volatility and a relatively short time period, daily price data is gathered and it is quoted in U.S. dollars for U.S. equity and euros for European equity. Dividends are added into the price data for both ETFs and indices, hence reflecting the gross total return data.

The validity of the data from Bloomberg Terminal (2020) is tested by comparing the results to the Capital IQs (2020) database. For the benchmark indices (S&P 500 and Stoxx 600), the same procedure is applied and the gross total return data is collected. There are 124 daily observations for each factor index/ETF in total during the studied period. All data is processed and calculated by utilizing Microsoft Excel-spreadsheet and R-programming language in R-studio.

3.2.1 Key information on factor indices

Table 4 presents the key information[3] on the studied factor indices, including the description of each index as well as the weights of the largest sectors. The number of constituents may change each time the index is rebalanced. The sector weights vary based on the daily price movements of stocks included in the index, as well as when the index is rebalanced, thus making the sector allocations change over the studied period. Table 4 shows that, on average, the value and small-cap factor indices were founded earlier than other factor indices.

***Table 4**. Key information on the factor indices*

Index	Description	Five Largest Sectors
1. CRSP US Large Cap Value Index	CRSP US Large Cap Value Index incorporates 336 value stocks in the U.S. market. The index is founded in 2012.	Health Care (20,64%), Financials (18,05%), Consumer Staples (12,09%), Industrials (11,43%), and Consumer Discretionary (8,09%).
2. Russell 1000 Value Index	Russell 1000 Value Index incorporates 838 value stocks in the U.S. market. The index is founded in 1987.	Financial Services, Health Care, Consumer Discretionary, Producer Durables and Technology.
3. S&P 500® Value Index	S&P 500® Value Index incorporates 390 value stocks in the U.S. market. The index is founded in 1992.	Health Care (20,6%), Financials (18,3%), Consumer Staples (10,7%), Industrials (9,5%), and Information Technology (8,7%).
4. MSCI Europe Enhanced Value Index	MSCI Europe Enhanced Value Index incorporates 149 value stocks in the European market. The index is founded in 2014.	Health Care (16,93%), Financials (15,68%), Consumer Staples (14,31%), Industrials (13,48%), and Consumer Discretionary (9,99%).
1. S&P SmallCap 600® Index	S&P SmallCap 600® Index incorporates 601 small-cap stocks in the U.S. market. The index is founded in 1994.	Industrials (18,1%), Financials (15,1%), Consumer Discretionary (14,8%), Information Technology (14,1%), and Health Care (13,2%).
2. Russell 2000 Index	Russell 2000 Index incorporates 2005 small-cap stocks in the U.S. market. The index is founded in 1984.	Financial Services, Health Care, Technology, Consumer Discretionary, and Producer Durables.
3. CRSP US Small Cap Index	CRSP US Small Cap Index incorporates 1361 small-cap stocks in the U.S. market. The index is founded in 2012.	Industrials (18,4%), Health Care (15,73%), Technology (15,30%), Consumer Discretionary (14,27%), and Financials (12,96%).

3 The key information has been gathered from the factsheets of the index providers on 21.7.2020. Due to this, the data illustrate the positions on the 30th of June 2020. Index providers update the factsheets at frequent intervals and thus the data collected on the 21st of July 2020 is no longer publicly available. The sector weights regarding the Russell 1000 Value Index and the Russell 2000 Index were not available.

4. MSCI EMU Small Cap Index	MSCI EMU Small Cap Index incorporates 432 small-cap stocks in the European market. The index is founded in 1998.	Industrials (21,53%), Financials (13,9%), Information Technology (11,99%), Real Estate (9,71%), and Health Care (9,37%).
1. MSCI USA Momentum Index	MSCI USA Momentum Index incorporates 125 momentum stocks in the U.S. market. The index is founded in 2013.	Health Care (31,74%), Information Technology (31,64%), Consumer Discretionary (11,11%), Communication Services (10,64%), and Real Estate (4,3%)
2. DW Technical Leaders Index	Dorsey Wright Technical Leaders Index incorporates 100 momentum stocks in the U.S. market. The index is founded in 2007.	Technology (30,28%), Industrials (22,93%), Financials (12,78%), Health Care (12,55%), and Consumer Services (10,89%).
3. JP Morgan US Momentum Factor Index	JP Morgan US Momentum Factor Index incorporates 266 momentum stocks in the U.S. market. The index is founded in 2017.	Technology (27,75%), Health Care (14,13%), Industrial Goods & Services (10,59%), Retail (8,95%), and Financial Services (7,39%)
4. MSCI Europe Momentum Index	MSCI Europe Momentum Index incorporates 125 momentum stocks in the European market. The index is founded in 2013.	Health Care (29,78%), Information Technology (12,46%), Industrials (11,31%), Consumer Discretionary (11%), and Utilities (10,97%).
1. MSCI USA Extended ESG Focus Index	MSCI USA Extended ESG Focus Index incorporates 346 ESG stocks in the U.S. market. The index is founded in 2018.	Information Technology (27,97%), Health Care (14,43%), Consumer Discretionary (11,04%), Communication Services (10,43%), and Financials (10,17%).
2. MSCI USA ESG Leaders Index	MSCI USA ESG Leaders Index incorporates 289 ESG stocks in the U.S market. The index is founded in 2001.	Information Technology (27,92%), Health Care (14,37%), Consumer Discretionary (11,03%), Communication Services (10,5%), and Financials (9,96%).
3. MSCI USA Extended ESG Leaders Index	MSCI USA Extended ESG Leaders Index incorporates 289 ESG stocks in the U.S. market. The index is founded in 2019.	Information Technology (27,92%), Health Care (14,37%), Consumer Discretionary (11,03%), Communication Services (10,5%), and Financials (9,96%)
4. MSCI Europe SRI Select Reduced Fossil Fuel Index	MSCI Europe SRI Select Reduced Fossil Fuel Index incorporates 113 ESG stocks in the European market. The index is founded in 2019.	Consumer Staples (16,95%), Financials (16,47%), Health Care (14,76%), Industrials (14,09%), and Consumer Discretionary (9,81%).
1. MSCI USA Sector Neutral Quality Index	MSCI USA Sector Neutral Quality Index incorporates 125 quality stocks in the U.S. market. The index is founded in 2014.	Information Technology (27,77%), Health Care (14,42%), Consumer Discretionary (10,92%), Communication Services (10,78%), and Financials (10,02%).
2. S&P 500® Quality Index	S&P500® Quality Index incorporates 100 quality stocks in the U.S. market. The index is founded in 2014.	Information Technology (40,8%), Health Care (23,3%), Consumer Staples (9%), Industrials (8,9%), and Consumer Discretionary (5,2%).
3. JP Morgan US Quality Factor Index	JP Morgan US Quality Factor Index incorporates 236 quality stocks in the U.S. market. The index is founded in 2017.	Technology (27,64%), Health Care (13,98%), Industrials Goods & Services (10,93%), Retail (8,93%), and Financial Services (7,14%).
4. MSCI Europe Sector Neutral Quality Index	MSCI Europe Sector Neutral Quality Index incorporates 125 quality stocks in the European market. The index is founded in 2014.	Health Care (16,27%), Financials (15,26%), Consumer Staples (14,87%), Industrials (13,06%), and Consumer Discretionary (9,85%).

Figure 6 presents the historical development of the price-to-earnings ratio (P/E) for all studied factor categories in the U.S. markets (Bloomberg Terminal 2020). The time period consists of the past four years starting from 01.01.2016 and ending 01.01.2020. The price to earnings ratio is calculated by using the last price of the month and the last full-year earnings. According to Figure 6, the MSCI USA Momentum Index and the S&P SmallCap 600®

Index have historically had a higher P/E ratio than the other factors. This indicates that the market is expecting these indices to have higher future earnings growth, which may persuade investors to pay more for companies included in these indices. The P/E ratio of the S&P 500® Quality Index has been historically relatively close with the P/E ratio of the MSCI USA ESG Leaders Index. The CRSP US Large Cap Value Index has had the lowest historical P/E, which is, however, consistent with the characteristics of value stocks.

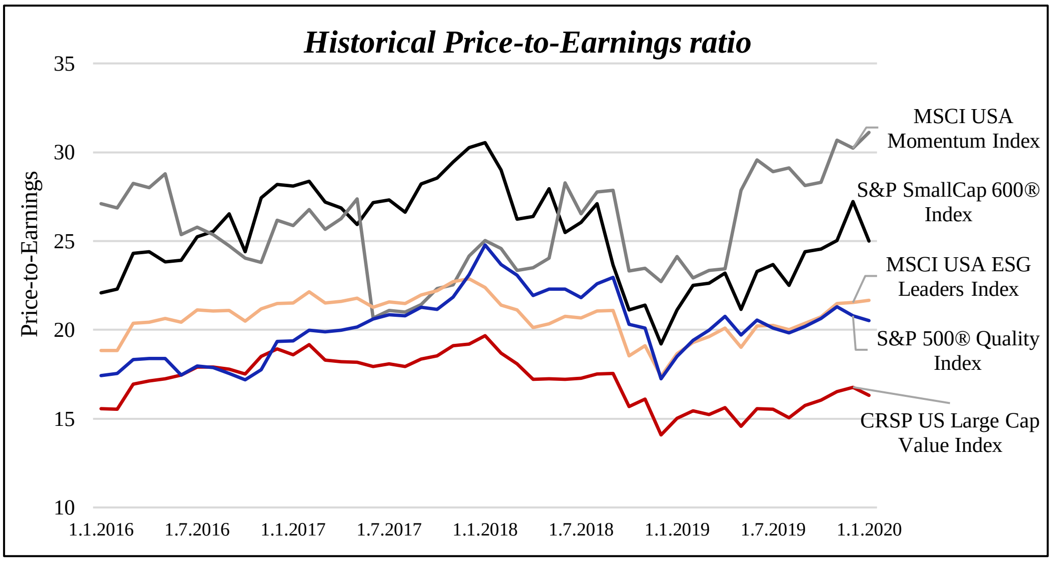

Figure 6. *Historical performance measured by P/E multiple*

Table 5 presents the relative multiples for the studied factor indices. Multiples in the table are calculated by applying the current (28.8.2020) price or enterprise value and the trailing 12-month (or last available) Earnings, Book value, Sales, EBIT, EBITDA, and Dividend. (Bloomberg Terminal 2020) Equity and enterprise-based multiples are chosen to achieve a holistic view when conducting the relative valuation for indices. Two main findings can be detected in Table 5. First, on average, the U.S. domiciled indices are valued higher than their European counterparts. This can also be observed from the dividend yield percentage, which is higher for European companies. Higher multiples indicate that investors are willing to pay a higher relative price for the securities. This could suggest that investors are expecting higher future cash flows (higher growth and/or margins) or consider the securities in the index less risky (smaller discount rate). Second, clear differences between the relative valuation of factors exist. The value index has, on average, the lowest valuation multiples, whereas momentum and size have the highest multiples. ESG and quality factors are relatively closely valued based on the multiples. Overall, it can be concluded that the relative values are above average with respect to their historical levels, which is partly due to the drop in earnings, sales, EBIT, EBITDA in 2020 due to the Covid-19 that inflates the multiples.

***Table 5**. Relative multiples for factor indices*

Factor	Index	P/E	P/B	EV/SALES	EV/EBIT	EV/EBITDA	Dividend Yield (%)
Value	CRSP US Large Cap Value Index	19,0	2,2	2,0	22,0	12,1	3,0
	Russell 1000 Value Index	21,4	2,2	2,2	26,7	13,5	2,6
	S&P 500® Value Index	19,7	2,1	1,9	25,0	12,8	2,9
	MSCI Europe Enhanced Value Index	51,0	1,0	1,1	19,2	8,3	3,3
Size	S&P SmallCap 600® Index	57,1	1,8	1,4	-	20,0	1,9
	Russell 2000 Index	-	2,0	1,8	-	28,6	1,6
	CRSP US Small Cap Index	45,4	2,3	2,1	-	24,5	1,6
	MSCI EMU Small Cap Index	36,7	1,4	4,2	18,9	33,6	2,0
Momentum	MSCI USA Momentum Index	39,1	8,1	4,1	34,4	23,4	0,9
	DW Technical Leaders Index	-	-	-	-	-	-
	JP Morgan US Momentum Factor Index	40,5	6,5	4,4	37,6	22,7	1,2
	MSCI Europe Momentum Index	35,5	4,1	4,3	28,8	18,2	1,7
ESG	MSCI USA Extended ESG Focus Index	27,8	4,0	3,0	28,2	17,4	1,7
	MSCI USA ESG Leaders Index	26,3	4,6	3,3	27,2	18,1	1,7
	MSCI USA Extended ESG Leaders Index	-	-	-	-	-	-
	MSCI Europe SRI Select Reduced Fossil Fuel Index	28,4	2,3	1,9	19,4	14,1	2,3
Quality	MSCI USA Sector Neutral Quality Index	26,0	5,5	3,6	22,6	17,7	1,6
	S&P 500® Quality Index	26,8	5,4	3,5	25,8	17,6	1,7
	JP Morgan US Quality Factor Index	23,9	6,2	3,4	24,7	16,9	1,9
	MSCI Europe Sector Neutral Quality Index	27,0	3,3	2,3	20,1	13,7	2,9

3.3 Construction methodology of factor indices

Index providers apply different methodologies to determine the weightings for companies in the index. In addition, different rules and requirements are set by index providers for the eligibility to be included in the index.[4] The formation of factor indices can endure a relatively

[4] The index-specific methodologies are reviewed and applied by using the latest methodologies of index providers provided on 21.7.2020 (CRSP 2020; FTSE Russell 2020b; S&P Dow Jones Indices 2020d; MSCI 2017a; S&P Dow Jones Indices 2020c; MSCI 2020e; MSCI 2017b; Nasdaq 2017; FTSE Russell 2020a; MSCI 2020d; MSCI 2019b; MSCI 2019a; MSCI 2017c; S&P Dow Jones Indices 2020b). Most index providers update the methodologies at frequent intervals and thus the data collected on the 21st of July 2020 may not be longer publicly available. Nevertheless, the main features of the methodology of index provider do not change very often.

complex process and is index provider specific. In this sub-section, the most important aspects of the formation process of an index are adduced. The main divergences between the index providers are reviewed to discern the differences between index providers.

The formation process of factor indices includes four main steps based on the review and assessment of the methodologies applied by the index providers. Figure 7 illustrates these main steps, which are further analyzed in the following sub-sections. In the first step, the equity universe is defined. In the second step, the variables are defined for factor classification and in the third step, the weighting methodology is applied. The fourth step illustrates the rebalancing cycle regarding the studied indices. The sub-section analyzes the practical aspects of forming an index and the main contributions related to the formation process of factor indices.

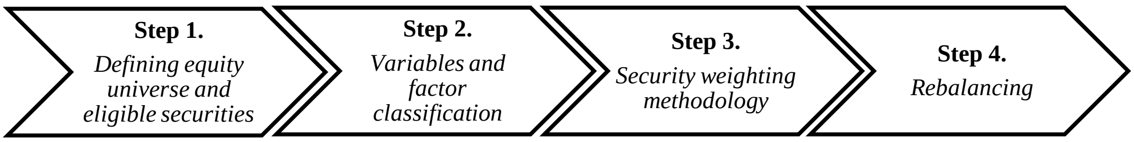

Figure 7. *The formation process of factor indices*

3.3.1 Defining equity universe and eligible securities

According to the review of methodologies, the definition of equity universe and eligible securities is index provider specific and tends to vary by the index provider. Common characteristics can still be identified to produce a review of this process. The equity universe is first defined by the index provider from which a more detailed investability screening process can be initiated. The definition of equity universe could include the company's listing exchange, headquarter location, country of incorporation, share types, and organization type. In general, based on the review, it could be concluded that all listed stocks in the targeted market area do fulfill the investable equity universe from which a more precise investability screening can be initiated. Generally, the qualification for equity universe is not very strict, and as an example, a company that has a headquarter in the U.S. usually qualifies to be included in the equity universe for indices investing in the U.S. In some cases, the applicable equity universe is based on the underlying parent index, an equity index without a factor tilt. Therefore, the eligible equity universe includes all the constituents that are included in the underlying parent index.

Investability screening further restricts the number of eligible securities. The definition of eligible securities and the requirements that security should pass is again subject to the internal process of an index provider. Depending on the index provider, security must pass various criteria. The market capitalization and free float-adjusted market capitalization are often considered criteria to comply with the minimum size requirement of indices. Liquidity and trading volume of security is also commonly considered in the investability screening process. On a general level, it can be concluded that the investability screening process is not especially strict and aims to remove the most illiquid stocks. This stage does not have as high impact as the following steps when considering the final allocation of constituents.

3.3.2 Variables and factor classification

The process of constructing the factor index can be initiated after the equity universe and eligible securities are defined. In the second step, the index providers define the desired variables that are suitable for factor classification. Furthermore, the number of variables used in the factor classification is disclosed. Table 6 presents the variables applied in the factor classification process by the largest factor indices measured by the AUM of ETFs following these indices[5].

Table 6. *Factor classifications*

Factor	Index	Factor Classification
Value	CRSP US Large Cap Value Index	Book-to-price, Future earnings-to-price, Historical earnings-to-price, Dividend-to-price, and Sales-to-price.
	Russell 1000 Value Index	Book-to-price.
	S&P 500® Value Index	Book value-to-price, Earnings-to-price, and Sales-to-price.
	MSCI Europe Enhanced Value Index	Price-to-book value, Price-to-forward earnings, and Enterprise value-to-cash flow from operations.
Size	S&P SmallCap 600® Index	Unadjusted market capitalization of $600 million to $2.4 billion. Float market capitalization of at least $300 million.
	Russell 2000 Index	The largest U.S. companies are put in a descending order (total market capitalization) and 1001-3000 are chosen in the index.

[5] The data is applied from factsheets and methodologies of index providers on 21.7.2020. (CRSP 2020; FTSE Russell 2020b; S&P Dow Jones Indices 2020d; MSCI 2017a; S&P Dow Jones Indices 2020c; MSCI 2020e; MSCI 2017b; Nasdaq 2017; FTSE Russell 2020a; MSCI 2020d; MSCI 2019b; MSCI 2019a; MSCI 2017c; S&P Dow Jones Indices 2020b).

	CRSP US Small Cap Index	U.S. companies that fall between the bottom 2-15 % of the investable market cap. There is no lower limit in market cap.
	MSCI EMU Small Cap Index	--
Momentum	MSCI USA Momentum Index	Stock's recent 12-month and 6-month price performance. The risk-adjusted momentum value is calculated.
	DW Technical Leaders Index	Intermediate and long-term price movements relative to a representative market benchmark.
	JP Morgan US Momentum Factor Index	Stocks 12-month local return divided by standard deviation of 12 months of daily local returns.
	MSCI Europe Momentum Index	Stock's recent 12-month and 6-month price performance. The risk-adjusted momentum value is calculated.
ESG[6]	MSCI USA Extended ESG Focus Index	The index is based on MSCI USA Index, from which the companies are selected by using 10 parameters with Barra open optimizer in combination with the Barra equity model. The aim of optimization process is to maximize the exposure to ESG factors.
	MSCI USA ESG Leaders Index	Companies must have an MSCI ESG rating of 'BB' or above and MSCI ESG controversies score of 3 or above to be eligible to the index. *
	MSCI USA Extended ESG Leaders Index	Companies must have an MSCI ESG rating of 'BB' or above and MSCI ESG controversies score of 3 or above to be eligible to the index. *
	MSCI Europe SRI Select Reduced Fossil Fuel Index	Companies must have an MSCI ESG rating of 'A' or above and MSCI ESG controversies score of 4 or above to be eligible to the index. *
Quality	MSCI USA Sector Neutral Quality Index	High Return-on-Equity (ROE), Low leverage and Low earnings variability.
	S&P 500® Quality Index	Return-on-Equity, Accruals ratio and Financial leverage ratio.
	JP Morgan US Quality Factor Index	ROE, Cash flow ROI, Free cash flow/sales, Cash flow interest cover, Free cash flow/Current liabilities, Cash flow/Total debt, Low volatility, Change in accruals, Balance sheet based operating accruals and Cash flow based operating accruals.
	MSCI Europe Sector Neutral Quality Index	High Return-on-Equity, Low leverage and Low earnings variability.

[6] From the MSCI USA Extended ESG Focus Index values-based exclusions include controversial weapons, tobacco, producers of or ties with civilian firearms, whereas climate change-based exclusions include oil sands and thermal coal. In addition, firms involved in severe business controversies and firms that do not have the ESG rating/ESG score or controversy score are excluded from the index.

The MSCI USA ESG Leaders Index as well as the MSCI USA Extended ESG Leaders Index excludes gambling, alcohol, tobacco, nuclear power, and weapons from the indices. The MSCI USA Extended ESG Leaders Index excludes also civilian firearms.

From the MSCI Europe SRI Select Reduced Fossil Fuel Index values-based exclusions include tobacco, alcohol, weapons, civilian firearms, adult entertainment, gambling, nuclear power, and genetically modified organisms. Climate change-based exclusions include thermal coal mining, unconventional oil and gas extraction, oil sands extraction, conventional oil and gas extraction, thermal coal-based power generation, oil and gas-based power generation, thermal coal reserves, and oil sands reserves.

***** MSCI's ESG rating offers a view of a company's exposure to ESG risks and how well the company manages the ESG criteria. The MSCI's rating consists of a seven-point-scale from 'AAA' to 'CCC', where 'AAA' represents the best rate (leader) whereas 'CCC' the worst rate (laggard). Rates are 'CCC', 'B', 'BB', 'BBB', 'A', 'AA', and 'AAA'. (MSCI 2020b)

* MSCI ESG controversies offer assessments of controversies related to the negative ESG impact of the company's services, commodities, and operations. The score varies between 0 to 10 where "0" is the most severe controversy.

Table 6 shows that different index providers and factor indices apply different variables when classifying factors and the number of variables applied in the process varies as well. The results seen in Table 6 should have extensive impacts on the final weightings of constituents in the indices.

3.3.3 Security weighting methodology

The security weighting methodology of stocks can be conducted after the desired variables are set. Generally, stocks are included in the index based on exposure to the defined variables, but the weighting methodologies can vary between indices. The weighting methodology of indices can be a relatively complex process and hold various steps. Therefore, the full replication and presentation of each weighting methodology go beyond the scope of this research. The objective is to analyze the main principles and categorize the weighting methodologies such that the main drivers and differences between indices can be recognized.

The weighting methodologies can vary between index providers and within the same index provider, and therefore, at least partially explain the performance differences between indices. The index specific weighting methodologies are presented below[7]. Almost all of the factor indices are free float-adjusted market capitalization weighted indices, except the MSCI USA Extended ESG Focus Index, which is only a market capitalization weighted index. In addition, the DW Technical Leaders Index (Momentum) does not disclose whether the index is float-adjusted or a market-capitalization based index.

- **Z - SCORE**

*CRSP US Large-Cap Value Index; S&P 500® Value Index; MSCI Europe Enhanced Value Index; MSCI USA Momentum Index; MSCI Europe Momentum Index; MSCI USA Sector Neutral Quality Index; S&P 500® Quality Index**;** MSCI Europe Sector Neutral Quality Index*

[7] The information is applied from methodologies of index providers on 21.7.2020 (CRSP 2020; FTSE Russell 2020b; S&P Dow Jones Indices 2020d; MSCI 2017a; S&P Dow Jones Indices 2020c; MSCI 2020e; MSCI 2017b; Nasdaq 2017; FTSE Russell 2020a; FTSE Russell 2015; MSCI 2020d; MSCI 2019b; MSCI 2019a; MSCI 2017c; S&P Dow Jones Indices 2020b). The security weighting methodology is not available for the MSCI EMU Small Cap Index.

Z-score is an often applied methodology when determining the factor tilt for a specific security. Z-score is a numerical measure that measures the number of standard deviations that the value is below or above the mean value of the studied measure. The z-score value of 0 indicates that the value is identical to the mean value of the studied sample size. On a normal distribution, 95% of the values are within +/- 1.96 standard deviations from the mean, and 99% of values within +/- 2.58 standard deviations. The z-score (Equation 2) can be calculated as follow:

$$Z = \frac{x-\mu}{\sigma} \quad \textbf{(2)}$$

$$x = Observed\ value$$
$$\mu = Mean\ of\ the\ sample$$
$$\sigma = Standard\ deviation\ of\ the\ sample$$

The z-score is calculated for all variables individually to determine the style characteristics of a company. The calculated z-scores are aggregated for each company and based on the score, the weighting of a stock can be determined. The market capitalization-weighted indices adjust the z-score based on the (free-float adjusted) market capitalization. This adjustment allows more weight on companies that have a larger (free-float adjusted) market capitalization and less for smaller companies even if the unadjusted z-score might be higher. If there is more than one variable used to determine the style characteristics, then the arithmetic average of the z-scores can be used to determine the final composite z-score, as shown in Equation 3 below:

$$A\ composite\ Z - Score = \frac{1}{N}(Z_{Variable\ 1} + Z_{Variable\ 2} \ldots + Z_{Variable\ N}) \quad \textbf{(3)}$$

As different sector weightings can widely affect the results, sector-neutral indices are constructed to make the results more comparable to the benchmark index. In sector-neutral indices, the weight of each sector in the factor index should be equal to the sector weight in the parent index. This is achieved by normalizing the weights of stocks within all sectors to achieve the weights of parent indices. The MSCI Europe Enhanced Value Index, MSCI USA Sector Neutral Quality Index, and MSCI Europe Sector Neutral Quality Index are sector-neutral indices.

There are different methodologies to construct the final factor indices after the z-score is calculated. For example, in the CRSP US Large Cap Value Index, the final index balancing is conducted with the rank approach after the stocks are scored based on the z-score. The CRSP US Large Cap Value Index assigns for each stock an average rank value, based on the z-scores. In the CRSP US Large Cap Value Index, a company with a mean score below 0.5 is categorized as growth, and a company with a mean score above 0.5 is categorized as value. Companies fully belong to either of these groups and are included in the index based on the average rank. In the S&P 500® Quality Index, stocks are ranked based on obtained quality scores and a targeted stock count of 100 stocks. The stocks that rank within the top 80% are automatically chosen for index inclusion. Then all stocks that are currently included in the index and are within the top 120 % of the target stock count (100) are chosen for index inclusion based on their quality score. Finally, if the stock count is not yet met, the last stocks are included based on the quality score. The maximum GICS sector weight restriction is set to 40%. As shown by these examples, the z-score by itself is not often enough to form the final factor weightings. A combination of the z-score approach and rank approach can be utilized to form the final weightings.

❖ RANK APPROACH

S&P SmallCap 600® Index; Russell 2000 Index; CRSP US Small Cap Index; DW Technical Leaders Index; JP Morgan US Momentum Factor Index; MSCI USA ESG Leaders Index; MSCI USA Extended ESG Leaders Index; MSCI Europe SRI Select Reduced Fossil Fuel Index; JP Morgan US Quality Factor Index

The rank approach is a relatively simple approach where stocks are simply ranked or ordinally arranged based on the value of a predetermined variable. Usually, only one variable is used to achieve the final factor score. Depending on the factor, the highest or the lowest values are applied when terminating the factor score. For example, when forming a size index, the stocks are ranked based on market capitalization from the largest to the smallest company in the equity universe. The final companies could be included in the index based on a predetermined threshold, for example, by including the smallest 20%.

The S&P SmallCap 600® Index is a sector-neutral index (Global Industry Classification Standard) and includes the top 600 companies by unadjusted market capitalization of $600 million to $2.4 billion and float market capitalization of at least $300 million. The index provider, however, does not provide further details on how the companies are included in the index. In the Russell 2000 Index, companies are ranked in descending order based on total market capitalization. The Russell 2000 Index includes the smallest 2000 companies out of 3000 companies based on market capitalization. In the CRSP US Small Cap Index, companies are ranked from the largest to the smallest based on the total market capitalization. The smallest 85%- 98% are included in the index. The DW Technical Leaders Index ranks the equity universe and the weights are decided based on the scores of each stock, however, the index provider does not offer a more detailed overview of weighting methodology. The index does not include any sector constraints. The JP Morgan US Momentum Factor Index and the JP Morgan US Quality Factor Index have an internal equation to decide the percentile rank for each stock (Equation 4). The weightings of the stocks are classified in accordance with the Industry Classification Benchmark (ICB). The percentile rank for stock i in sector k is calculated as:

$$p_i = 100 * \frac{1+c_i+0.5_{f_i}}{1+N}, \forall i \in k \tag{4}$$

c_i *is the amount of stocks in sector k with factor values less attractive as the factor value of the* i^{th} *stock*

f_i *is the amount of stocks with an identical factor value to stock i (excluding itself)*

N *is the total amount of eligible stocks in sector k*

In the MSCI USA ESG Leaders Index and the MSCI USA Extended ESG Leaders Index, stocks are ranked based on the ESG rating, ESG trend, current index membership, industry adjusted ESG scores, and free float-adjusted market capitalization. This is conducted for each sector separately. The minimum cumulative industry coverage is set to 45% from the Global Industry Classification Standard sector of the regional Parent Index. The MSCI Europe SRI Select Reduced Fossil Fuel Index contains the minimum cumulative sector coverage of 22.5%.

- **COMPOSITE VALUE SCORE AND NON-LINEAR PROBABILITY METHOD**

Russell 1000 Value Index

The composite value score (CVS) is the final score used to describe the stock's factor characteristics. CVS is calculated by combining and weighting the scores of prechosen variables that are used to describe the factor characteristic. The score for variables can be achieved, for example, by using the rank or z-score approach. A non-linear probability function is applied to CVS distribution to assign the final weights for each stock. The term probability is applied to imply the probability that a company has a certain style characteristic based on the applied variables. The non-linear probability method is applied to divide a large number of companies in the parent index into value and growth sub-indices that have opposite characteristics. This methodology is applied in the Russell 1000 value and growth indices. For example, a low CVS score is an indication of a growth stock, and a stock with a high CVS score can be considered as a value stock. A probability of 0 indicates a whole membership in the growth factor, whereas a probability of 1 indicates a full membership in the value factor. The market capitalization of stocks is taken into account and approximately 35% of the market value is fully included both in the growth and value indices. The rest, the middle range, including 30% of the market value is included in both value and growth indices and weighted according to the value probability score. In practice, this means, for example, that a CVS score of 0.4 assigns a value probability score of 0.1. Therefore, 10% of the weight in the parent index would be assigned to the value index and 90% of the weight in the parent index to the growth index. The weight in growth and value should always sum to 100 percent and hence the market capitalization will always match the larger parent index. Figure 8 below presents the non-linear probability function utilized to assign weights on value and growth indices.

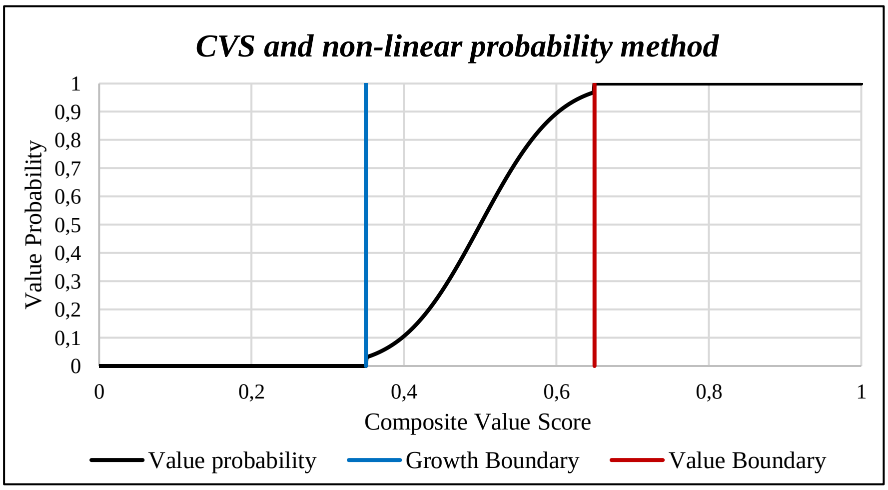

Figure 8. *Non-linear probability function*

❖ STYLE BASKETS

S&P 500® Value Index

In the S&P 500 Value Index, the composite value scores are first gathered by applying the z-score approach. After the composite value score is calculated for each stock, stocks can be ranked based on their composite scores, and the style basket approach is used to decide the final weights for stocks in the index. Stocks are ranked into three different baskets. The first basket is the growth basket (33% of index market cap), the second basket is the blended basket (34% of index market cap), holding both growth and value characteristics, and the third basket (33% of index market cap) is the value basket. Instead of including all stocks into the factor index by multiplying the composite score with market cap weights, more pure value factor indices can be constructed by including the stocks from the value basket into the index. In addition, from the blended basket, stocks are distributed to both growth and value indices based on their distance from the midpoint of growth and value baskets. Figure 9 illustrates the concept of the style baskets.

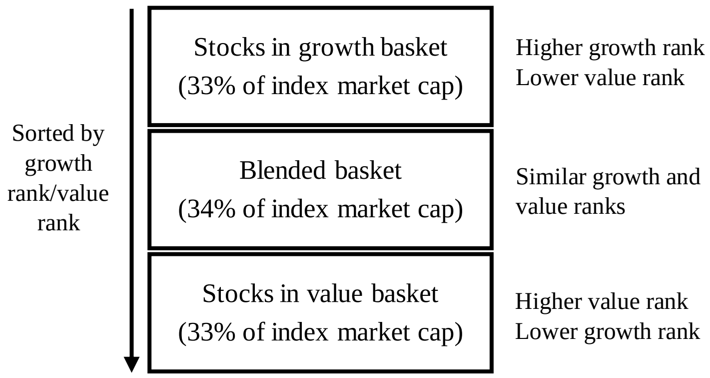

Figure 9. *Style baskets*

❖ OPTIMIZATION

MSCI USA Extended ESG Focus Index

Factor index can be formed by utilizing optimization, but it is a relatively complex and opaque process. The MSCI USA Extended ESG Focus Index applies two main steps in the optimization process. In the first step, the optimization constraints are set. The MSCI USA Extended ESG Focus Index apply 10 different constraints. The main principle is to have exposure to higher ESG scores while maintaining a similar return and risk characteristics as the parent index. The optimization maximizes the exposure to ESG-scores while keeping the tracking error at a given level. The second and last step is determining the portfolio by running the simulation using Barra Open Optimizer with Barra Equity Model. Optimization uses the eligible equity universe and optimizes the portfolio based on the specified objective and taking into account the determined constraints. The MSCI USA Extended ESG Focus Index is a sector-neutral index.

3.3.4 Rebalancing

The fourth and final step is the rebalancing of factor indices. Index providers maintain and review the indices at regular intervals to maintain the desired factor characteristics. The rebalancing process includes re-assessment of the eligibility of each stock to be included in the index as well as balancing the weights of eligible stocks. The rebalancing frequency varies between index providers and indices and thus can also partly explain the performance of the index. The rebalancing frequency usually fluctuates between annually, semi-annually, and quarterly depending on the index. Table 7 presents the rebalancing frequency regarding the studied indices[8].

Table 7. *Rebalancing frequency*

Quarterly	
In March, June, September, and December	CRSP US Large Cap Value Index S&P 500® Value Index S&P SmallCap 600® Index CRSP US Small Cap Index DW Technical Leaders Index JP Morgan US Momentum Factor Index JP Morgan US Quality Factor Index
In February, May, August, and November	MSCI USA Extended ESG Focus Index* MSCI USA ESG Leaders Index MSCI USA Extended ESG Leaders Index MSCI Europe SRI Select Reduced Fossil Fuel Index

[8] The information is applied from factsheets and methodologies of index providers on 21.7.2020 (CRSP 2020; FTSE Russell 2020b; S&P Dow Jones Indices 2020d; MSCI 2017a; S&P Dow Jones Indices 2020c; MSCI 2020e; MSCI 2017b; Nasdaq 2017; FTSE Russell 2020a; MSCI 2020d; MSCI 2019b; MSCI 2019a; MSCI 2017c; S&P Dow Jones Indices 2020b).
* The changes of rebalancing are effective at the beginning of March, June, September, and December.
** The rebalancing may also occur if the market volatility is really high.
*** Russell indices and the MSCI EMU Small Cap Index review the indices also on a quarterly basis including IPOs if occurred.

Semi-annually		
In May and November	⇨	MSCI Europe Enhanced Value Index MSCI EMU Small Cap Index*** MSCI USA Momentum Index** MSCI Europe Momentum Index** MSCI USA Sector Neutral Quality Index MSCI Europe Sector Neutral Quality Index
In June and December	⇨	S&P 500® Quality Index
Annually		
In June	⇨	Russell 1000 Value Index*** Russell 2000 Index***

3.4 Description of the research methodology

The methodology of this research is to quantitatively analyze the performance of factor investing during the first six months of the Covid-19 crisis. The methodology of this thesis is divided into two main sections. The first section analyzes the studied factor indices and ETFs by utilizing different performance and statistical measures. The objective is to obtain a comprehensive view of the performance of the studied factors. The studied performance and statistical measures are absolute return, excess return, tracking error, correlation, and Welch's t-test. In addition, the regression analysis and the return contribution analysis are utilized to analyze the effect of sector performance and allocations on the total returns of ETFs.

In the second section, academic pure long-only and long-short factor portfolios are formed, and the performance is benchmarked against the studied market capitalization-weighted factor indices. Pure factor portfolios are formed purely based on the factor characteristics. As the free-float of stocks or other major constraints are not taken into account, these portfolios reflect more pure factor exposures than the examined factor indices. Pure factor portfolios are formed since for most market participants, the liquidity is not restricting the investment decisions when investing in the S&P 500 or Stoxx 600 firms. The methodology of pure factor portfolios reflects the practices derived from the academic literature, and therefore, pure factor portfolios serve as a good benchmark for the studied factor indices. Various studies (e.g., Plyakha, Uppal, and Vilkov 2012; Bolognesi, Torluccio, and Zuccheri 2013; Blitz 2016; MSCI 2020c) have identified that equally-weighted indices outperform market-cap-weighted counterparts at least during normal market conditions. For this reason, pure factor portfolios are also formed by applying equal weighting methodology (1/n-weights) for each stock.

3.4.1 *Performance and statistical measures*

The performance of the studied indices is measured on an absolute basis for all periods separately. The absolute return is measured by simply calculating the total return for the studied time periods, and the return is then compared to the market return (S&P 500 and Stoxx 600 indices). The excess returns are calculated by subtracting the total return of a factor index from the total return of the market index for each period. If the return of the index is higher than the return of the market index, the factor index is considered to generate excess return.

An important aspect of the thesis is to study the actual performance of factor investing through ETFs. Therefore, the performance of factor ETFs is benchmarked against the factor indices. Tracking error is the standard deviation of the difference between the actual return and the corresponding return of the benchmark index. For passive investment products, such as index ETFs, the lowest amount of tracking error is desired. Tracking error can occur for various reasons, the most common being the small difference in holdings and management fees. (BlackRock 2020a) Equation 5 is applied to calculate the tracking error, where (R_i) is the return of an investment and (R_b) is the return of a benchmark index.

$$Tracking\ Error = stdev(R_i - R_b) \qquad \textbf{(5)}$$

The correlation is a statistical measure that explains the degree of relative movement between two securities. Correlation among two securities can vary between -1 and +1, where a positive value indicates a positive correlation, and on the contrary, a negative value indicates a negative correlation. A value of 0 indicates no correlation, and a value of +/-1 indicates perfect positive or negative correlation. (Bodie, Kane, and Marcus 2005, 1031-1032) According to Markowitz's (1952) modern portfolio theory, investors prefer to have securities that have a low or negative correlation to increase the diversification benefits. The correlation of factor indices is studied in this research to apprehend if there are any diversification benefits to be gained. Equation 6 presents the formula for correlation, where ($Cov\ (r_x,\ r_y)$) represents the covariances of returns of X and Y securities and $(\sigma_x\sigma_y)$ represent the standard deviations of X and Y securities, respectively.

$$Correlation = \frac{Cov\ (r_x, r_y)}{\sigma_x\sigma_y} \tag{6}$$

Welch's (1947) t-test is used to determine if there is a significant difference between the mean returns of samples. Welch's t-test assumes unequal variances and/or sample sizes, making it more feasible with financial data than the traditional Student's t-test. The statistical significance is determined by the degrees of freedom and with the use of t-statistics. A null hypothesis is that there is no difference between the means of samples. Welch's t-test is conducted by applying Equation 7, where $\overline{X_i}$ is the sample mean, N_i is the sample size, s_i is the standard deviation of the sample, v is the degrees of freedom, v_1 is the $N_1 - 1$, and v_2 is the $N_2 - 1$. (Delacre, Lakens, and Leys 2017)

$$Welch's\ T\ Stat = \frac{\overline{X_1 - X_2}}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}} \qquad v = \frac{\left(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}\right)\text{^}2}{\frac{s_1^4}{N_{1}^2{}_{v_1}} + \frac{s_2^4}{N_{2}^2{}_{v_2}}} \tag{7}$$

The simple linear regression analysis is applied when analyzing the results. This statistical method is used for estimating the relationship between a dependent variable and an independent variable. The regression equation is presented below (Equation 8), where y_i is the dependent variable, β_0 is the intercept, which is also known as a constant that is the expected mean value of Y when X=0. The value following the intercept $\beta_1 x_i$ is the coefficient of the independent variable that is used to estimate the dependent variable y_i. ε_i is the error term that is the difference between the estimated value and the true value. (Yan and Su 2009, 1-5)

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \tag{8}$$

In addition to the presented measures, the sector return contribution analysis is conducted when analyzing the results. The sector contribution to the total returns is calculated by applying Equation 9, where n is the number of sectors, w_i the weight of the sector, R_i the return of the sector and $w_i R_i$ is the contribution to the portfolio's return. (Bacon and Wright 2012)

$$R = \sum_{i=1}^{i=n} w_i R_i \tag{9}$$

3.4.2 Methodology of pure factor portfolios

The construction methodology of pure academic factor portfolios is presented in this sub-section. The presented methodology (e.g., equity universe, variables, etc.) of pure factor portfolios is obtained by utilizing the R-programming language. The performance of pure factor portfolios is studied during the same time period (2nd of January 2020 to 30th of June 2020) as factor indices to make the results comparable and benchmarked against the performance of studied factor indices. The performance of European pure factor portfolios is denominated in euros, whereas the U.S. pure factor portfolios are denominated in U.S. dollars. The returns reflect theoretical returns since transaction costs are not taken into account to make the results comparable with the studied factor indices. In addition, no rebalancing takes place since the studied time period is relatively short.

The methodology of pure factor portfolios includes various steps that are partially connected to the presented methodologies of the studied factor indices. The first step is to define the equity universe from which further screening can be applied. The equity universe for pure factor portfolios consists of all companies included in the parent indices S&P 500 and Stoxx 600. Equity screening is conducted for companies included in the equity universe. In equity screening, the variables used to define factor characteristics are applied. Different variables and a different number of variables can be used to define the factor characteristics of a company. The variables used to define different factors are chosen based on the literature review and shown in Table 8. The ESG factor is excluded from pure factor portfolios since the ESG data and ratings are dependent on third-party service providers, and the data is not available for this purpose. The values for variables are applied ex-ante the Covid-19 crisis presenting the position at the end of 2019. Therefore, the results are not distorted by the crisis and are more objective. For all the defined variables, the z-scores (Equation 2) are calculated separately, and for multivariable factors (Value, Quality), an aggregated z-score is applied (Equation 3). Companies in the equity universe are ranked from the highest to the lowest based on the z-scores. Depending on the factor characteristics, the lowest or highest

1/3 of companies with the desired factor characteristics are included in the portfolio according to the definition assessed in the literature review. The 1/3 company weighting methodology follows the main principles according to Fama and French (1993) and Blitz (2012).

Table 8. *Variables for pure factor portfolios*

Factor	Variables		Weight
Value	P/E	P/B	50/50
Size	Market capitalization		100
Momentum	The past 52-week performance		100
Quality	ROE-%	EBIT-%	50/50

The academic pure factor portfolios are constructed by applying both equally-weighted as well as market capitalization-weighted methodologies to analyze the differences in returns between these methodologies and to achieve extensive results. Various studies (e.g., Plyakha et al. 2012; Bolognesi et al. 2013; Blitz 2016; MSCI 2020c) have argued that equally-weighted indices outperform the market capitalization-weighted indices at least during normal market conditions. In an endeavor to achieve a holistic view, both long-short as well as long-only strategies are applied to market capitalization and equally-weighted methodologies to complement the results. Figure 10 illustrates the complete construction process for pure factor portfolios, starting from the equity screening to the implementation of the methodology.

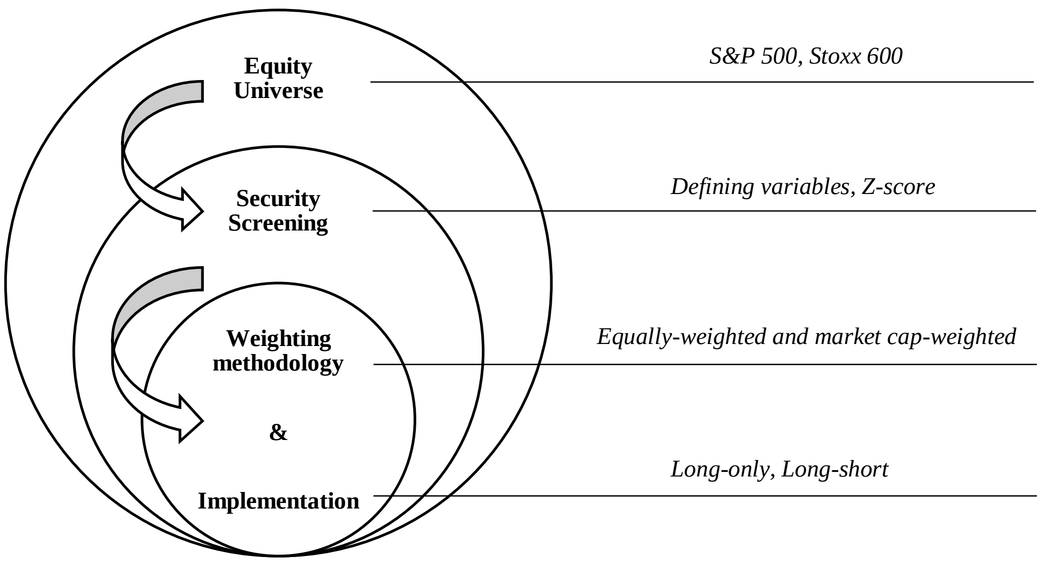

Figure 10. *The construction process of pure factor portfolios*

4. EMPIRICAL ANALYSIS AND RESULTS

This section starts by first laying out the large picture of the performance of style factor indices in the U.S. and Europe during the full sample period. Figures 11 and 12 visualize the cumulative returns of the five largest factor indices in each market area measured by AUM of ETFs. The S&P 500 is included as a benchmark index for U.S. indices and Stoxx 600 for European companies. The cumulative returns are indexed to start from the 2nd of January (the first trading day of the year) and end on the 30th of June. The markets bottomed on the 23rd of March 2020 and started a rapid recovery. As an interesting observation, on the same day, the Fed announced that it will increase its balance sheet by investing in treasury securities as well as agency mortgage-backed securities in *"the amounts needed"* (Figure 5). This indicates that the Central banks' actions played an essential role in stabilizing and supporting the recovery of the stock markets during the Covid-19.

By analyzing Figure 11, the momentum index has been the strongest performer from the beginning of the period, whereas the size (small-cap) index has performed the weakest of all indices in the U.S. market in absolute terms. An interesting finding is that ESG and quality factor indices have performed relatively in parallel with the S&P 500 index with a small tracking error. Value investing has performed relatively poorly throughout the studied period.

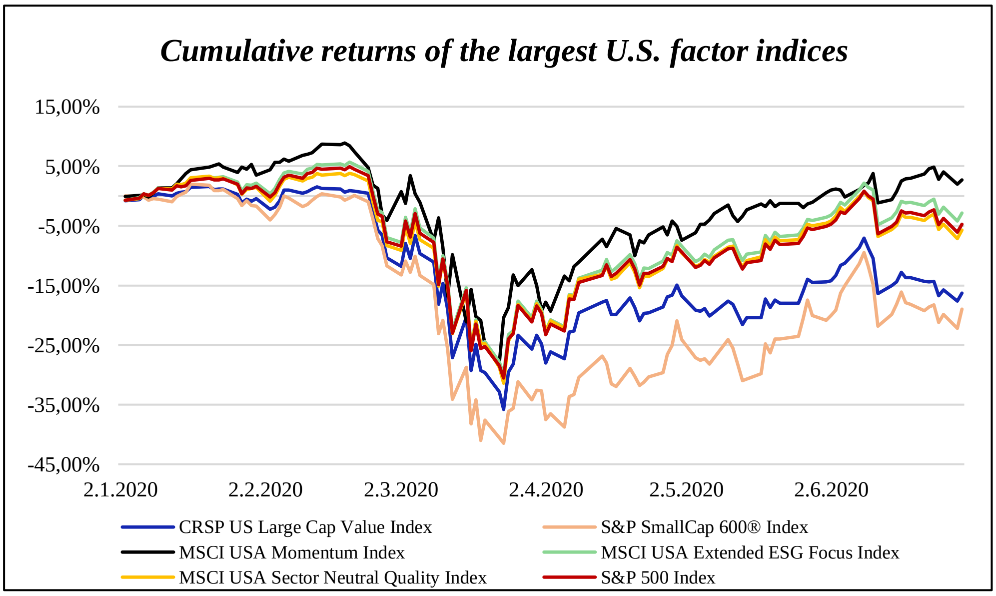

Figure 11. *Cumulative returns of the largest U.S. factor indices*

Momentum and ESG indices have outperformed the S&P 500 benchmark index, although ESG only with a small margin, whereas value, quality, and size factor indices have underperformed the benchmark index, respectively. In addition to the presented findings, Figure 11 shows that the outperformance of the momentum index has been stable throughout the period. In the European market (Figure 12), the results are very similar when compared to the performance of the U.S. factor indices. The main difference is that in Europe, the size (small-cap) factor index outperformed the value factor index, and the quality index outperformed the benchmark index in terms of absolute returns. The outperformance of momentum, quality, and ESG factor indices relative to the market has been stable during the whole studied period. Overall, it can be concluded that factor indices investing in Europe have not recovered as well as in the U.S. Factor indices presented in Figures 11 and 12 reflect only the cumulative returns of the largest indices and represent only a small portion of all indices included in the study.

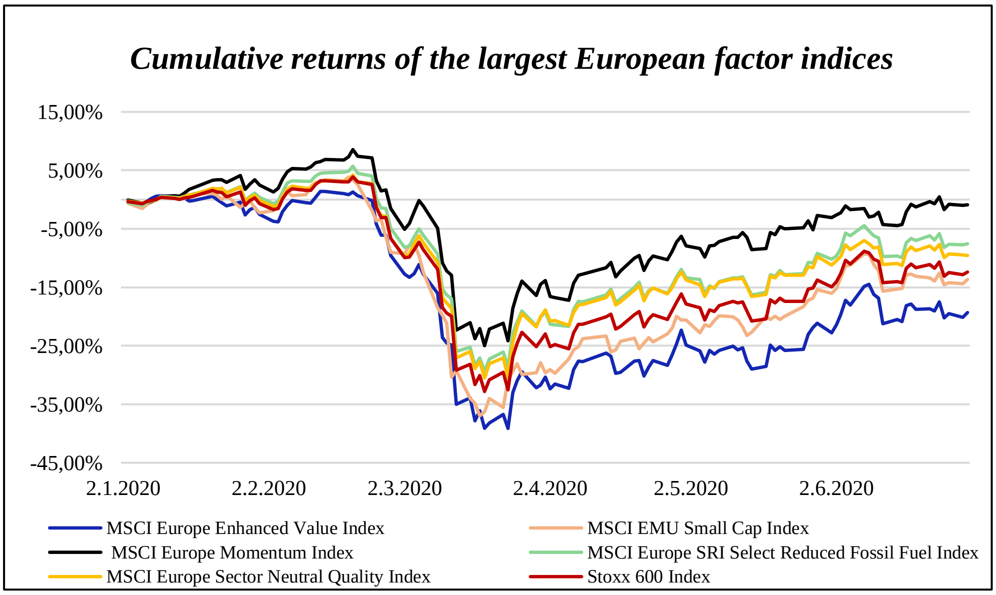

Figure 12. *Cumulative returns of the largest European factor indices*

Figure 13 presents the sector performance of the MSCI USA and MSCI Europe indices during the sample period. The sector performance is analyzed by utilizing the MSCI USA and MSCI Europe indices since GICS sector performance was not available for the S&P 500 and Stoxx 600 indices. The performance of sectors is presented to analyze whether the sector performance can contribute to the overall performance. This analysis is conducted by comparing the sector allocations of the studied ETFs and indices to the performance of sectors. The sector performance is denominated in euros for the MSCI Europe Index and U.S. dollars for the MSCI USA Index. Figure 13 utilizes the broader industry classification standard, GICS sector level 2. The MSCI Europe and MSCI USA indices have different sector weightings, and therefore, the returns of sectors do not equally contribute to the total return of indices. The total return for the MSCI Europe is -12.45 % and -2.20 % for the MSCI USA during the full sample period.

As can be observed from Figure 13, most sectors performed similarly in both Europe and the U.S., but larger differences can be observed as well. The performance of the MSCI USA Index was notably better than the performance of the MSCI Europe Index, especially in retail where the difference of returns is 29.3%, software and services 23.6%, media and entertainment 30.6%, real estate 12.0%, consumer services 16.7%, and automobiles and components 50.1%. On the contrary, the performance of the MSCI Europe Index was better in utilities 11.9% and in diversified financials 5.4%. Overall, the sector performance was significantly better in the U.S. than in the European market area.

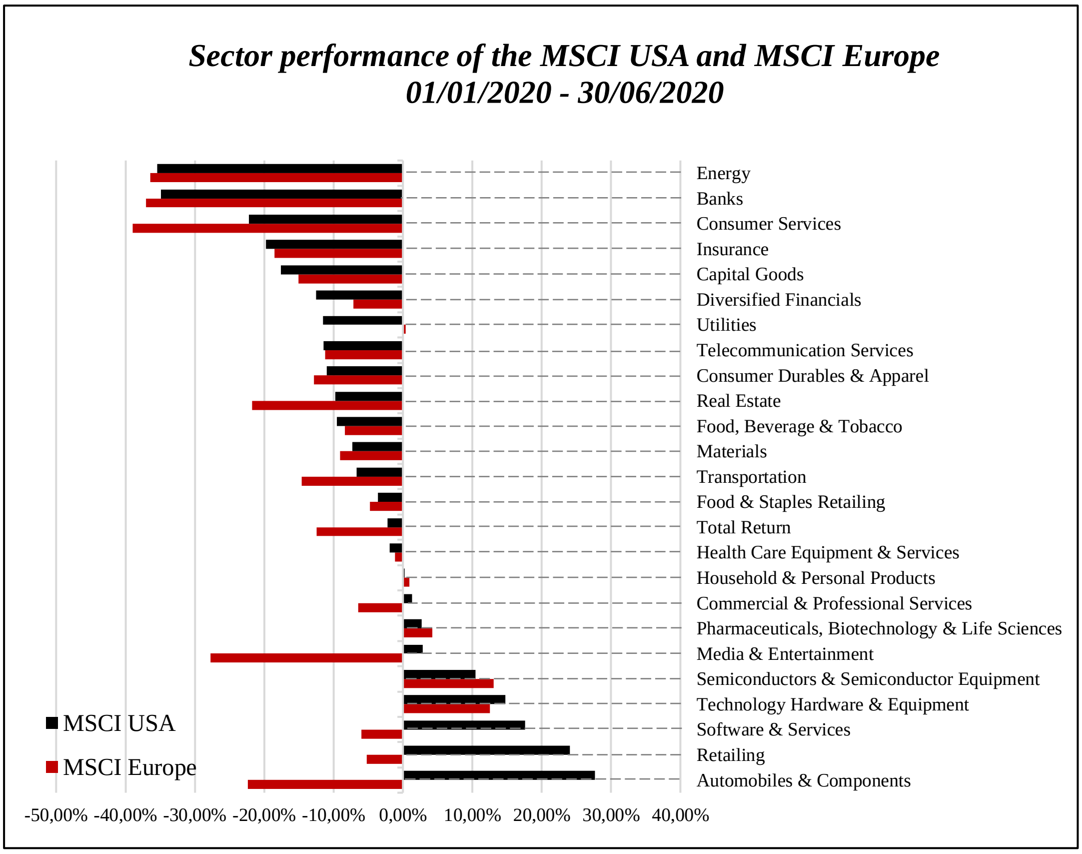

Figure 13. *The sector performance of the MSCI USA and MSCI Europe indices*

4.1 Absolute returns and tracking error

Table 9 represents the absolute returns of factor and market indices during the bear, recovery, and full sample periods. The excess returns are presented as well to find out whether the factor index has outperformed or underperformed the market index in absolute terms. Table 9 is a color-coded column by column to visualize the differences in returns. The indices in the table are categorized in the following order: value, size, momentum, ESG, quality, and market benchmark indices. At first, the results are analyzed on a high level and then a more detailed analysis of the main differences is conducted. The results are compared to the hypotheses created according to the literature review and plausible explanations for the performance are presented based on the construction methodology of indices.

"European indices lagged the U.S. counterparts thoroughly, especially during the recovery phase."

Table 9. *Absolute returns of factor and market benchmark indices*

Index	Full Period	Bear	Recovery	Full Period	Bear	Recovery
	Absolute return			Excess Return		
CRSP US Large Cap Value	-15,82 %	-36,35 %	20,43 %	-11,92 %	-2,81 %	-6,91 %
Russell 1000 Value	-16,53 %	-38,16 %	21,70 %	-12,64 %	-4,62 %	-5,65 %
S&P 500® Value	-15,81 %	-36,75 %	20,71 %	-11,91 %	-3,21 %	-6,63 %
MSCI Europe Enhanced Value	-19,78 %	-39,52 %	20,39 %	-7,19 %	-4,98 %	0,44 %
S&P SmallCap 600®	-17,85 %	-41,55 %	28,75 %	-13,95 %	-8,01 %	1,41 %
Russell 2000	-12,91 %	-40,79 %	31,99 %	-9,01 %	-7,25 %	4,65 %
CRSP US Small Cap	-11,52 %	-41,79 %	34,56 %	-7,62 %	-8,25 %	7,21 %
MSCI EMU Small Cap	-14,06 %	-37,67 %	25,00 %	-1,47 %	-3,13 %	5,06 %
MSCI USA Momentum	4,90 %	-33,55 %	31,88 %	8,80 %	-0,01 %	4,54 %
DW Technical Leaders	4,47 %	-33,75 %	33,27 %	8,36 %	-0,21 %	5,92 %
JP Morgan US Momentum Factor	1,65 %	-34,29 %	32,01 %	5,55 %	-0,75 %	4,66 %
MSCI Europe Momentum	-0,58 %	-29,34 %	22,28 %	12,01 %	5,20 %	2,33 %
MSCI USA Extended ESG Focus	-1,88 %	-33,49 %	28,68 %	2,01 %	0,05 %	1,34 %
MSCI USA ESG Leaders	-2,52 %	-34,15 %	27,66 %	1,38 %	-0,61 %	0,32 %
MSCI USA Extended ESG Leaders	-2,52 %	-34,15 %	27,66 %	1,38 %	-0,61 %	0,32 %
MSCI Europe SRI Select Reduced Fossil Fuel	-7,79 %	-31,62 %	20,11 %	4,80 %	2,92 %	0,17 %
MSCI USA Sector Neutral Quality	-4,90 %	-33,76 %	26,61 %	-1,00 %	-0,22 %	-0,74 %
S&P 500® Quality	-2,85 %	-31,00 %	25,40 %	1,05 %	2,54 %	-1,95 %
JP Morgan US Quality Factor	-2,77 %	-32,49 %	27,05 %	1,12 %	1,05 %	-0,30 %
MSCI Europe Sector Neutral Quality	-9,57 %	-32,44 %	19,99 %	3,02 %	2,11 %	0,04 %
S&P 500 Index	-3,90 %	-33,54 %	27,34 %			
Stoxx 600 Index	-12,59 %	-34,54 %	19,94 %			

* Table 9 illustrates the absolute returns of factor indices, and the excess return is the difference between the return of the factor index and the S&P 500 or Stoxx 600 index.

Table 9 shows that the S&P 500 index outperformed the Stoxx 600 benchmark index during the full sample period with a margin of 8.69%[9]. The outperformance occurred, especially during the recovery market, whereas these benchmark indices performed very similarly during the bear market. Two main explanations for the outperformance of the S&P 500 index during the recovery market can be found. First, companies with large market capitalization outperformed companies with a small market capitalization in the U.S., whereas the reverse held in Europe. Companies with larger market capitalization have a higher weight in the index, thus contributing more to the total return since both of these indices are market capitalization-weighted. Second, sector performance was overall stronger in the U.S. (Figure 13), and also the sector mix yielded better for the S&P 500 index (Appendix 2). European factor indices[10] lagged especially during the recovery phase, whereas the differences were more subtle during the bear market. It can be concluded that during the full sample period, the European factor indices underperformed their U.S. counterparts due to the relatively weak performance on the recovery market.

"The value factor indices performed the worst, whereas the momentum factor indices were able to generate positive returns."

Generally, the value factor performed the worst, closely followed by the size factor when the full sample period is considered. The performance of size factor indices was the weakest during the bear market but the second strongest after momentum during the recovery market. Quality and ESG factors performed relatively parallel with the market index, whereas the momentum factor indices clearly outperformed both market and other factor indices. The poor performance of value indices was expected based on the literature review since value stocks are considered riskier and have been underperforming in past crises as well. In addition, value strategy has been underperforming since 2007 due to the ongoing technological revolution related to the technology sector that is now harvesting and delivering the promises given during the IT-bubble (Meredith 2019).

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9 The S&P 500 index generated the return of -10.47% whereas the Stoxx 600 index yielded -10.87% when applying 1/N-weights for the full sample period.

10 MSCI Europe Enhanced Value Index, MSCI EMU Small Cap Index, MSCI Europe Momentum Index, MSCI Europe SRI Select Reduced Fossil Fuel Index*, MSCI Europe Sector Neutral Quality Index

***** The performance of the MSCI Europe SRI Select Reduced Fossil Fuel Index is calculated by using the net total return data due to the non-availability of gross total return data.

"Momentum, ESG, and quality factors were able to produce excess returns, whereas value and size were mainly outperformed by the benchmark indices."

All indices declined in a relatively same manner during the bear market, except size and value, which declined even further than other indices. The largest differences in performance occurred during the recovery market, where momentum and size factors were the strongest recoverers. The value factor indices performed the weakest during the recovery phase, followed by quality factor indices. Ang (2014, 444) argued that factor investing is inherently riskier and thus generates excess returns over longer periods but can underperform during short time periods and especially during bad times such as market crashes. The results regarding the excess returns of momentum, ESG, and quality factor indices are evidence against this argument, indicating that these factors are less risky, although the academic background of these factors is less grounded.

"Factors performed as anticipated based on the hypotheses formed from the academia except the momentum factor that produced opposite results"

The results regarding the performance of the value factor indices are in line with the formed hypothesis based on earlier findings of Chen and Zhang (1998), Zhang (2005), Winkelmann et al. (2013), Campbell et al. (2013), Ang (2014, 230), Lee et al. (2014), and Yamani and Swanzon (2014) who argued that the value factor underperforms especially during market shocks and value factor premiums are compensation for taking a higher risk. However, conflicting evidence exists (see, e.g., Lakonishok et al. 1994, Bird and Whitaker 2003, Pätäri et al. 2010, Hwang and Rubesam 2013, and Pätäri et al. 2016).

Size factor indices performed exactly as expected based on the hypothesis drawn from the academic literature. According to Arshanapalli and Nelson (2007), Switzer (2010), Kilbert and Subramanian (2010), and Winkelmann et al. (2013), small-cap portfolios are more sensitive to economic shocks due to the higher systematic risk and thus perform poorly during market crashes, but should rebound faster than the market during bull markets.

The strongest performance of the momentum factor during the crisis is conflicting with previous academic studies conducted by Daniel and Moskowitz (2016), Cheema and Nartea

(2017), and Maheshwari and Dhankar (2017). The hypothesis based on academic studies indicates that the momentum factor should underperform during a crisis and especially during the market recovery. However, the results regarding the performance of momentum factor indices were the opposite during the Covid-19 as the momentum factor proved to be the strongest performer. However, it should be noted that most of the previous crises have been based on endogenous financial shocks, while the Covid-19 is exogenous and arrives outside from the financial system.

According to Nofsinger and Varma (2014), Lins et al. (2017), and Albuquerque et al. (2020), companies with a high ESG profile tend to have a lower risk and higher return during a crisis, and especially during the bear market. The results of this study neither support nor rejects this hypothesis. Generally, it can be concluded that the ESG factor performed in parallel or slightly outperformed the market index when the full sample period is considered.

A scarce amount of academic literature exists related to the performance of quality factor during the market crashes, and therefore, no comprehensive hypothesis could be formed. However, based on the studies of George (2002) and Asness et al. (2019), quality factor should be more defensive and thus implicitly perform relatively well during crises. The results of this study indicate that the quality factor indices perform in a relatively similar manner with the benchmark index both in bear and recovery markets.

"The returns of indices within the same factor category are relatively close, but a few larger differences do occur."

The methodologies of factor indices differ between index providers, which leads to slightly different weightings of stocks and returns between indices. Few main observations can be assessed when looking at the returns between indices within the same factor category. The largest difference in returns occurs within the size factor category. The S&P SmallCap 600® Index lagged other U.S. size indices in terms of performance. The difference in performance is notable and the poor performance is present, especially in the recovery market. The probable explanation is a relatively larger weight in sectors that underperformed, e.g., financials (15.1%) and a smaller weight in sectors that outperformed, e.g., technology

(14.1%) during the crisis[11]. The main difference between the S&P SmallCap 600 Index and other size indices is that the classification methodology is based on *"unadjusted market capitalization of $600 million to $2.4 billion"*, whereas other size indices are based on size rankings of companies. This classification methodology is not as flexible as ranking based methodologies, leading to include larger companies in the index during market crashes as the market values of all companies decrease. The methodology of the S&P SmallCap 600 Index is bounded to market capitalization and not on the size rankings of companies. This should have caused the index to include larger companies than other size indices during the rebalancing on March 2020.

The JP Morgan US Momentum Factor Index underperformed relative to the other U.S. momentum factor indices. This could be at least partly explained by the sector allocation and, for example, a smaller weight on the technology sector (27.75%) compared to other studied U.S. momentum indices. Compared to other momentum indices, the JP Morgan US Momentum Factor Index also has more than double the number of constituents included in the index. This should lead to an allocation that has a higher weight on stocks with a smaller market capitalization that underperformed relative to large-capitalization stocks in the U.S. In addition, the JP Morgan US Momentum Factor Index is a sector-neutral index, unlike the DW Technical leaders Index that outperformed the JP Morgan US Momentum Index. This could indicate that the DW Technical leaders Index had a more favorable sector allocation during the Covid-19. The MSCI USA Momentum Index does not disclose the sector neutrality. Finally, the JP Morgan US Momentum Index defines momentum stocks according to the past 12 months' performance, whereas most of the studied momentum indices apply both 6 and 12 months price performance. These elements should jointly explain the difference in performance derived from the methodology of indices.

In the quality category, the MSCI USA Sector Neutral Quality Index underperformed during the full sample period as well as the bear market but performed in line with peers during the recovery market. The sector allocation or the number of constituents should not explain the relatively poor performance (Table 4) of the MSCI USA Sector Neutral Quality Index. The

11 The weights are gathered from Table 4 and illustrates the positions on the 30th of June 2020.

lagging performance of the index could be explained by the classification methodology. The MSCI USA Sector Neutral Quality Index has different variables and a number of variables relative to other quality indices.

"Factor ETFs underperformed their benchmark factor indices when the full sample period is considered, although the differences are subtle."

Table 10 represents the absolute returns of the factor ETFs that follows the factor indices. ETFs are listed in the table in the same order as the indices they follow (Table 9). Table 10 illustrates the actual performance of what an investor would actually achieve when investing in factor ETFs. The first three columns present the absolute performance of ETFs, whereas the last three columns show the excess return that is the difference of return between the ETF and the specific factor index that the ETF follows. As can be observed, the performance of ETFs differs from the performance of factor indices. All ETFs underperformed their benchmark indices when the full sample period is considered, but the differences in performance are relatively small. Three ETFs stand-out, however, when the excess return of the full sample period is considered. The iShares MSCI EMU Small-Cap UCITS, iShares Edge MSCI Europe Momentum Factor UCITS, and iShares Edge MSCI Europe Quality Factor UCITS resulted in the poorest performances relative to their benchmark indices. As a common element, all of these three ETFs have relatively high expense ratios and a European focus.

***Table 10**. Absolute returns of ETFs*

	Full Period	Bear	Recovery	Full Period	Bear	Recovery
ETF	Absolute Return			Excess Return		
Vanguard Value	-15,97 %	-36,33 %	20,10 %	-0,15 %	0,02 %	-0,33 %
iShares Russell 1000 Value	-16,63 %	-38,39 %	21,63 %	-0,09 %	-0,22 %	-0,07 %
iShares S&P 500 Value	-15,92 %	-36,76 %	20,65 %	-0,11 %	-0,01 %	-0,07 %
iShares Edge MSCI Europe Value Factor UCITS	-19,93 %	-39,73 %	21,15 %	-0,15 %	-0,21 %	0,77 %
iShares Core S&P Small-Cap	-17,96 %	-41,53 %	28,97 %	-0,11 %	0,02 %	0,22 %
iShares Russell 2000	-13,02 %	-40,82 %	32,24 %	-0,12 %	-0,03 %	0,25 %
Vanguard Small-Cap	-11,69 %	-42,05 %	34,64 %	-0,17 %	-0,26 %	0,08 %
iShares MSCI EMU Small-Cap UCITS	-14,52 %	-37,36 %	25,52 %	-0,46 %	0,31 %	0,52 %
iShares Edge MSCI USA Momentum Factor	4,72 %	-33,81 %	31,96 %	-0,18 %	-0,26 %	0,08 %
Invesco DWA Momentum	4,23 %	-33,98 %	33,21 %	-0,23 %	-0,24 %	-0,06 %
JPMorgan U.S. Momentum Factor	1,53 %	-33,96 %	31,45 %	-0,12 %	0,32 %	-0,56 %
iShares Edge MSCI Europe Momentum Factor UCITS	-1,26 %	-29,35 %	21,62 %	-0,68 %	0,00 %	-0,66 %

iShares ESG Aware MSCI USA	-1,93 %	-33,62 %	28,73 %	-0,05 %	-0,12 %	0,05 %
Xtrackers MSCI USA ESG Leaders Equity	-2,68 %	-33,92 %	27,48 %	-0,16 %	0,23 %	-0,18 %
iShares ESG MSCI USA Leaders	-2,52 %	-34,07 %	27,72 %	0,00 %	0,08 %	0,06 %
iShares MSCI Europe SRI UCITS	-7,96 %	-31,38 %	21,51 %	-0,18 %	0,24 %	1,40 %
iShares Edge MSCI USA Quality Factor	-5,00 %	-33,86 %	26,58 %	-0,11 %	-0,09 %	-0,02 %
Invesco S&P500 Quality	-2,95 %	-31,23 %	25,34 %	-0,10 %	-0,23 %	-0,06 %
JPMorgan U.S. Quality Factor	-2,80 %	-32,64 %	27,17 %	-0,03 %	-0,16 %	0,12 %
iShares Edge MSCI Europe Quality Factor UCITS	-10,15 %	-32,49 %	20,38 %	-0,58 %	-0,05 %	0,39 %

* Table 10 illustrates the absolute returns of ETFs, and the excess return is the difference between the return of ETF and the ETF specific factor index.

Surprisingly, many of the studied ETFs outperformed the benchmark factor index, either in bear or recovery periods. In addition, most factor ETFs produced higher returns than the market indices (S&P 500/Stoxx 600) even when the costs are considered. This observation is against the findings of Malkiel (2014), who stated that when considering the practical aspects, the track record of real factor ETFs is quite spotty on a general level compared to the market portfolio. In addition, Malkiel (2014) argues that factor investing has been seen more as a marketing gimmick.

"Tracking error is the highest in the size category, higher for European ETFs, and the expense ratio seems to contribute to the tracking error."

Table 11 presents the tracking error of ETFs relative to their benchmark factor indices as well as the expense ratios of ETFs. The expense ratio illustrates ETFs' yearly total expenses, including acquired fund fees and expenses, foreign taxes and other expenses, and management fees. The tracking error is generally higher for European ETFs relative to U.S. ETFs when the full sample period is considered. A higher expense ratio and lower AUM of ETFs negatively contribute to the tracking error (consistent with Chu 2011 and Tsalikis and Papadopoulos 2019). The average size of the U.S. ETFs is considerably larger than the average size of the European ETFs (Appendix 1), consistent with Tsalikis and Papadopoulos (2019).

The tracking error increases during the bear market and is generally higher than during the recovery market. This indicates that during highly volatile times, the tracking error widens, which is consistent with the findings of Singh and Kaur (2016). The tracking error is the highest in the size factor category, and the interpretation should be logical. Small-cap stocks are more illiquid (Amihud 2002), causing the trading of stocks to be more burdensome and thus increasing the tracking error. Tracking error is the lowest in the value factor category. This should be explained by the higher volume and the size of the value ETFs making them more liquid. According to Singh and Kaur (2016) and Tsalikis and Papadopoulos (2019), there is a positive and statistically significant relationship between the tracking error and the AUM of ETFs, indicating a lower tracking error for larger funds. The same phenomena can be observed in this study by comparing the AUM of ETFs (Table 3) and tracking errors (Table 11).

Table 11. *Tracking errors and expense ratios*

ETF	Full Period	Bear	Recovery	Expense Ratio
	Tracking Error			
Vanguard Value	0,12 %	0,20 %	0,10 %	0,04 %
iShares Russell 1000 Value	0,12 %	0,25 %	0,09 %	0,19 %
iShares S&P 500 Value	0,13 %	0,26 %	0,09 %	0,18 %
iShares Edge MSCI Europe Value Factor UCITS	0,34 %	0,41 %	0,37 %	0,25 %
iShares Core S&P Small-Cap	0,33 %	0,73 %	0,13 %	0,06 %
iShares Russell 2000	0,48 %	1,07 %	0,16 %	0,19 %
Vanguard Small-Cap	0,28 %	0,60 %	0,13 %	0,05 %
iShares MSCI EMU Small-Cap UCITS	0,39 %	0,51 %	0,43 %	0,58 %
iShares Edge MSCI USA Momentum Factor	0,11 %	0,21 %	0,08 %	0,15 %
Invesco DWA Momentum	0,15 %	0,22 %	0,14 %	0,62 %
JPMorgan U.S. Momentum Factor	0,37 %	0,81 %	0,16 %	0,12 %
iShares Edge MSCI Europe Momentum Factor UCITS	0,32 %	0,35 %	0,38 %	0,25 %
iShares ESG Aware MSCI USA	0,15 %	0,20 %	0,16 %	0,15 %
Xtrackers MSCI USA ESG Leaders Equity	0,16 %	0,26 %	0,14 %	0,10 %
iShares ESG MSCI USA Leaders	0,68 %	1,16 %	0,62 %	0,10 %
iShares MSCI Europe SRI UCITS	0,34 %	0,48 %	0,36 %	0,20 %
iShares Edge MSCI USA Quality Factor	0,19 %	0,40 %	0,11 %	0,15 %
Invesco S&P500 Quality	0,10 %	0,15 %	0,09 %	0,19 %
JPMorgan U.S. Quality Factor	0,18 %	0,28 %	0,14 %	0,12 %
iShares Edge MSCI Europe Quality Factor UCITS	0,37 %	0,49 %	0,38 %	0,25 %

* Table 11 illustrates the tracking error of ETFs relative to their benchmark factor indices.

Three ETFs stand-out with a relatively high tracking error, iShares Russell 2000, JPMorgan U.S. Momentum Factor, and iShares ESG MSCI USA Leaders. A high tracking error of these ETFs occurred during the bear market when the market volatility was the highest. The high tracking error of these ETFs was partly caused by individual trading days when the tracking error was especially high, thus raising the standard deviation for the full sample period.

"The differences in mean returns between the samples were not statistically significant, according to Welch's t-test"

Welch's t-test is conducted to determine if there is a significant difference between the mean returns of samples. Welch's t-test is conducted for factor ETFs and the corresponding market indices as well as between the largest factor ETFs both in the U.S. and Europe measured by the AUM of ETFs. The results showed that none of the returns do differ between the samples in a statistically significant manner at the 95% confidence level, which means that there are no intrinsic differences between the examined means of the samples. When considering factor ETFs and benchmark indices, the highest t-value of 0.34 was tested between the Ishares Edge MSCI Europe Momentum Factor UCITS ETF and Stoxx 600 with the p-value of 0.73 (v=240). The difference in mean returns between these samples was 0.093 percentage per day. In the U.S., the highest t-value of -0.29 was tested between the Ishares Russell 1000 Value ETF and S&P500 with the p-value of 0.77 (v=243). The difference in mean returns between these samples was 0.11 percentage per day. Between the largest U.S. factor ETFs, the highest t-value of -0.47 was measured between the Vanguard Value ETF and Ishares Edge MSCI USA Momentum Factor ETF. The p-value is 0.64 (v=244) and the difference in mean returns was 0.18 percentage per day. In Europe, the highest t-value of -0.516 was measured between the Ishares Edge MSCI Europe Value Factor UCITS ETF and Ishares Edge MSCI Europe Momentum Factor UCITS ETF with the p-value of 0.606 (v=226), and the difference in mean returns was 0.15% per day. The results of Welch's t-test are consistent when considering observations already made above in Tables 9 and 10. The lowest p-value was measured between the samples with the largest difference in mean returns when taking into account the variance of the returns.

4.2 Sector return contribution analysis

The objective of this sub-section is to study the contribution of sector performance to the total returns of factor ETFs during the studied time period. The results are presented for factor ETFs, as the sector data was not available for factor indices, however, the results for factor indices should be analogous to the results of ETFs due to relatively small tracking error as presented in Table 11. The sector return contribution analysis is conducted to study to what extent the sector performance contributes to the total returns of ETFs and how sector weights are allocated between factors at the beginning of the crisis. The sector allocations and constituents of ETFs were not available for all ETFs as of 31st of December 2019, and therefore, 13 factor ETFs managed by Blackrock were selected for further analysis. The results are analyzed by utilizing the narrowest sector classification standard, GICS level 1. For each ETF, only equity is taken into account, whereas all else is excluded, e.g., cash, cash collateral, money market instruments, etc.

Table 12 presents the sector weights of the ETFs as of 31st of December 2019[12]. The sector weights are selected according to the methodology of indices and represent the sector weights of the ETFs at the end of 2019. This date is chosen to obtain the sector weights at the beginning of the studied time period. The table utilizes the following abbreviations for sectors: Communication (Com.), Consumer Discretionary (Con D.), Consumer Staples (Con S.), Energy (Ener.), Financials (Finan.), Healthcare (Hcar.), Industrials (Indu.), Information Technology (Inf Te.), Materials (Mate.), Real Estate (Re E.), and Utilities (Util.). The last two rows in Table 12 represent the performance of the sectors for the MSCI USA Index and MSCI Europe Index during the full sample period starting from the 2nd of January 2020 and ending on the 30th of June 2020. The sector allocations within factor categories are relatively similar between the U.S. ETFs but differ compared to European ETFs.

Table 12. *Sector weights of the ETFs as of 31.12.2019*

ETF	Com.	Con D.	Con S.	Ener.	Finan.	Hcar.	Indu.	Inf Te.	Mate.	Re E.	Util.
iShares Russell 1000 Value	8,1 %	5,8 %	8,8 %	8,2 %	23,8 %	12,9 %	9,6 %	6,3 %	4,3 %	5,2 %	6,6 %
iShares S&P 500 Value	7,6 %	5,5 %	9,5 %	7,9 %	21,4 %	18,3 %	9,8 %	7,7 %	2,8 %	3,2 %	6,2 %
iShares Edge MSCI Europe Value.	4,2 %	9,4 %	14,5 %	6,7 %	18,0 %	13,8 %	13,7 %	6,1 %	7,3 %	1,5 %	4,3 %
iShares Core S&P Small-Cap	2,0 %	13,7 %	4,3 %	4,3 %	16,9 %	12,3 %	17,6 %	13,9 %	5,0 %	7,4 %	2,2 %
iShares Russell 2000	2,3 %	10,8 %	3,0 %	3,2 %	17,5 %	18,2 %	15,9 %	13,5 %	3,9 %	7,8 %	3,7 %
iShares MSCI EMU Small-Cap.	7,0 %	8,5 %	3,2 %	3,1 %	13,3 %	8,5 %	21,0 %	11,5 %	7,2 %	11,4 %	5,1 %
iShares Edge MSCI USA Mom.	7,4 %	6,1 %	8,5 %	0,0 %	6,7 %	10,7 %	6,7 %	26,3 %	4,0 %	11,5 %	12,0 %
iShares Edge MSCI Europe Mom.	1,5 %	10,9 %	11,9 %	0,4 %	11,9 %	20,9 %	17,0 %	9,9 %	4,0 %	1,9 %	9,2 %
iShares ESG Aware MSCI USA	9,6 %	9,0 %	7,0 %	4,1 %	12,2 %	13,9 %	9,9 %	24,2 %	3,0 %	3,2 %	3,7 %
iShares ESG MSCI USA Leaders	10,3 %	10,4 %	7,1 %	3,9 %	12,1 %	14,0 %	9,1 %	23,4 %	2,8 %	3,2 %	3,3 %
iShares MSCI Europe SRI.	4,5 %	10,1 %	15,5 %	0,8 %	19,3 %	13,5 %	14,9 %	9,1 %	8,0 %	1,9 %	2,1 %
iShares Edge MSCI USA Qual.	10,4 %	10,2 %	7,0 %	4,1 %	12,8 %	13,9 %	9,1 %	23,2 %	2,6 %	3,2 %	3,2 %
iShares Edge MSCI Europe Qual.	4,5 %	10,1 %	13,5 %	6,8 %	18,0 %	13,6 %	13,8 %	6,1 %	7,4 %	1,5 %	4,4 %

[12] The sector weights are gathered from publicly available ETFs factsheets. (BlackRock 2020b; 2020c; 2020d; 2020e; 2020f; 2020g; 2020h; 2020i; 2020j; 2020k; 2020l; 2020m; 2020n).

*MSCI USA Index (TR)	0,0 %	11,2 %	-5,8 %	-35,4 %	-23,6 %	0,6 %	-13,6 %	15,5 %	-7,3 %	-9,8 %	-11,6 %
*MSCI Europe Index (TR)	-15,8 %	-17,2 %	-5,7 %	-36,5 %	-25,5 %	3,4 %	-13,7 %	2,9 %	-9,1 %	-21,8 %	0,4 %

*Total sector returns 02.01.2020 - 30.06.2020.

Table 13 presents the estimated sector performance of ETFs, calculated by applying the sector weights at the beginning of the studied period and multiplying the weights by the total return of the sector during the whole period. The returns of sectors are summed together, thus resulting in the estimated sector performance. The actual performance of the ETFs (the absolute returns of ETFs from Table 10) is included as well to analyze the difference between the estimated return and the actual performance of ETFs. The difference between the estimated and actual returns should be explained by the methodology of factor indices, e.g., factor tilt, restrictions, rebalancing, security weighting methodology, etc. However, it should be underlined that the relationship between the performance of factor ETFs and sectors is strongly interrelated, and part of total returns is based on the sector selection of factors. This denotes that the sector allocation is an essential part of the factor tilt.

Table 13. *Estimated sector performance vs. actual performance*

ETF	Estimated Sector Performance	Actual Performance
iShares Russell 1000 Value	-10,22 %	-16,63 %
iShares S&P 500 Value	-9,03 %	-15,92 %
iShares Edge MSCI Europe Value.	-12,33 %	-19,93 %
iShares Core S&P Small-Cap	-5,74 %	-17,96 %
iShares Russell 2000	-5,66 %	-13,02 %
iShares MSCI EMU Small-Cap.	-12,63 %	-14,52 %
iShares Edge MSCI USA Mom.	-0,97 %	4,72 %
iShares Edge MSCI Europe Mom.	-8,05 %	-1,26 %
iShares ESG Aware MSCI USA	-2,19 %	-1,93 %
iShares ESG MSCI USA Leaders	-1,92 %	-2,52 %
iShares MSCI Europe SRI.	-10,98 %	-7,96 %
iShares Edge MSCI USA Qual.	-2,17 %	-5,00 %
iShares Edge MSCI Europe Qual.	-12,51 %	-10,15 %

Generally, when the overall performance is considered in Table 13, it can be concluded that the estimated return of sectors is higher than the actual performance, especially in the value and size category, relatively equal for ESG and quality, and lower in the momentum category. This indicates that the formation methodology of factor indices, the factor tilt, affects the performance within the sectors since the estimated and actual performance of

ETFs differs. It should be noted that the sector allocation of ETFs fluctuates during the sample period and is not fully comparable to the allocation at the beginning of the period. According to Brière and Szafarz (2017a; 2018), factor investing is superior for capturing risk premiums and can boost the returns during normal market environments but can underperform sector investing during crises. The relatively poor performance of European sectors reflects in the returns of European factor ETFs. In Appendix 3, regression analysis is conducted to visualize the relationship between the estimated sector performance and the actual performance of ETFs. Appendix 3 shows that the sector performance has explanatory power on the actual performance of ETFs in all factor categories except in size, thereby indicating that small market capitalization stocks are not dependent on the performance of the sectors in which they operate during this crisis. However, the sample size is too small for drawing robust conclusions.

Tables 14 and 15 show the detailed sector allocations between factor ETFs. The sector weights are collected as of 31.12.2019, illustrating the positions at the beginning of the period. The absolute sector return contribution of ETFs is presented in Table 14, which shows that the financial sector had the largest absolute negative contribution to the returns of ETFs, followed by energy and industrials. On the opposite side, information technology and healthcare generally had an absolute positive contribution to the returns of ETFs. In the U.S., consumer discretionary also contributed positively to the returns. The total sector return equals to the estimated sector performance (sector weight multiplied by the MSCI GICS 1 level sector return).

***Table 14**. Absolute sector return contribution*

ETF	Com.	Con D.	Con S.	Ener.	Finan.	Hcar.	Indu.	Inf Te.	Mate.	Re E.	Util.	Total
iShares Russell 1000 Value	0,0 %	0,7 %	-0,5 %	-2,9 %	-5,6 %	0,1 %	-1,3 %	1,0 %	-0,3 %	-0,5 %	-0,8 %	-10,2 %
iShares S&P 500 Value	0,0 %	0,6 %	-0,5 %	-2,8 %	-5,0 %	0,1 %	-1,3 %	1,2 %	-0,2 %	-0,3 %	-0,7 %	-9,0 %
iShares Edge MSCI Europe Value.	-0,7 %	-1,6 %	-0,8 %	-2,4 %	-4,6 %	0,5 %	-1,9 %	0,2 %	-0,7 %	-0,3 %	0,0 %	-12,3 %
iShares Core S&P Small-Cap	0,0 %	1,5 %	-0,3 %	-1,5 %	-4,0 %	0,1 %	-2,4 %	2,2 %	-0,4 %	-0,7 %	-0,3 %	-5,7 %
iShares Russell 2000	0,0 %	1,2 %	-0,2 %	-1,1 %	-4,1 %	0,1 %	-2,2 %	2,1 %	-0,3 %	-0,8 %	-0,4 %	-5,7 %
iShares MSCI EMU Small-Cap.	-1,1 %	-1,5 %	-0,2 %	-1,1 %	-3,4 %	0,3 %	-2,9 %	0,3 %	-0,7 %	-2,5 %	0,0 %	-12,6 %
iShares Edge MSCI USA Mom.	0,0 %	0,7 %	-0,5 %	0,0 %	-1,6 %	0,1 %	-0,9 %	4,1 %	-0,3 %	-1,1 %	-1,4 %	-1,0 %
iShares Edge MSCI Europe Mom.	-0,2 %	-1,9 %	-0,7 %	-0,2 %	-3,0 %	0,7 %	-2,3 %	0,3 %	-0,4 %	-0,4 %	0,0 %	-8,0 %
iShares ESG Aware MSCI USA	0,0 %	1,0 %	-0,4 %	-1,4 %	-2,9 %	0,1 %	-1,3 %	3,8 %	-0,2 %	-0,3 %	-0,4 %	-2,2 %
iShares ESG MSCI USA Leaders	0,0 %	1,2 %	-0,4 %	-1,4 %	-2,8 %	0,1 %	-1,2 %	3,6 %	-0,2 %	-0,3 %	-0,4 %	-1,9 %
iShares MSCI Europe SRI.	-0,7 %	-1,7 %	-0,9 %	-0,3 %	-4,9 %	0,5 %	-2,0 %	0,3 %	-0,7 %	-0,4 %	0,0 %	-11,0 %
iShares Edge MSCI USA Qual.	0,0 %	1,1 %	-0,4 %	-1,4 %	-3,0 %	0,1 %	-1,2 %	3,6 %	-0,2 %	-0,3 %	-0,4 %	-2,2 %
iShares Edge MSCI Europe Qual.	-0,7 %	-1,7 %	-0,8 %	-2,5 %	-4,6 %	0,5 %	-1,9 %	0,2 %	-0,7 %	-0,3 %	0,0 %	-12,5 %

Table 15 presents the sector return contribution relative to the MSCI USA and MSCI Europe benchmark indices. The U.S. value ETFs had the highest weight on energy and financial sectors, which underperformed during the Covid-19 crisis. In addition, the U.S. value ETFs had the underweight on information technology that outperformed during the crisis. The combined overweight on poor performing sectors and underweight on outperforming sectors resulted in poor performance. A similar pattern can be observed in the size category, although less vigorously. ESG and Quality ETFs were relatively neutral, and no distinct sector bets can be seen, thereby resulting in a relatively similar performance with benchmark indices. Momentum ETFs had the underweight on energy and financial sectors. This sector mix was favorable and contributed positively to the total returns of momentum ETFs. Appendix 4 shows the sector bets compared to benchmark indices, including the weights of benchmark indices as of 31.12.2019.

Table 15. *Sector contribution relative to the benchmark*

ETF	Com.	Con D.	Con S.	Ener.	Finan.	Hcar.	Indu.	Inf Te.	Mate.	Re E.	Util.	Total
iShares Russell 1000 Value	0,0 %	-0,5 %	-0,1 %	-1,4 %	-2,6 %	0,0 %	-0,1 %	-2,7 %	-0,1 %	-0,2 %	-0,4 %	-8,0 %
iShares S&P 500 Value	0,0 %	-0,5 %	-0,1 %	-1,3 %	-2,0 %	0,0 %	-0,1 %	-2,4 %	0,0 %	0,0 %	-0,3 %	-6,8 %
iShares Edge MSCI Europe Value.	0,0 %	0,1 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,1 %
iShares Core S&P Small-Cap	0,0 %	0,4 %	0,2 %	0,0 %	-0,9 %	0,0 %	-1,2 %	-1,5 %	-0,2 %	-0,4 %	0,1 %	-3,5 %
iShares Russell 2000	0,0 %	0,1 %	0,2 %	0,3 %	-1,1 %	0,0 %	-0,9 %	-1,5 %	-0,1 %	-0,4 %	-0,1 %	-3,4 %
iShares MSCI EMU Small-Cap.	-0,4 %	0,3 %	0,6 %	1,3 %	1,2 %	-0,2 %	-1,0 %	0,2 %	0,0 %	-2,2 %	0,0 %	-0,2 %
iShares Edge MSCI USA Mom.	0,0 %	-0,4 %	-0,1 %	1,5 %	1,5 %	0,0 %	0,3 %	0,4 %	-0,1 %	-0,8 %	-1,0 %	1,3 %
iShares Edge MSCI Europe Mom.	0,5 %	-0,1 %	0,1 %	2,3 %	1,6 %	0,2 %	-0,4 %	0,1 %	0,3 %	-0,1 %	0,0 %	4,4 %
iShares ESG Aware MSCI USA	0,0 %	-0,1 %	0,0 %	0,0 %	0,2 %	0,0 %	-0,1 %	0,1 %	0,0 %	0,0 %	0,0 %	0,0 %
iShares ESG MSCI USA Leaders	0,0 %	0,1 %	0,0 %	0,1 %	0,2 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,3 %
iShares MSCI Europe SRI.	0,0 %	0,0 %	-0,1 %	2,2 %	-0,3 %	0,0 %	-0,2 %	0,1 %	-0,1 %	-0,1 %	0,0 %	1,5 %
iShares Edge MSCI USA Qual.	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,1 %
iShares Edge MSCI Europe Qual.	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	0,0 %	-0,1 %

4.3 Relative valuation

In this sub-section, the results are further analyzed by utilizing relative valuation metrics. Price to earnings ratio (P/E) and earning per share (EPS) estimates of all factor indices are analyzed. The P/E ratio and EPS estimates are calculated by applying the trailing next 12 months Bloomberg mean analyst consensus earnings estimates[13]. The EPS estimates are indexed to start from 100 to make the estimates more comparable. The price component of the P/E ratio is the daily closing price for the index. All the data in this sub-section is quoted

[13] The data is gathered on the 2nd of October 2020.

in U.S. dollars except the European ESG factor index (MSCI Europe SRI Select Reduced Fossil Fuel Index) in euros due to the non-availability of U.S. dollar quotations.

The price returns of the factor indices can be explained by the change of the expected future earnings (EPS) or by the change of how much investors are willing to pay for the future earnings (P/E). In premise, the value of an asset should be the present value of future cash flows discounted with an appropriate discount rate. Therefore, if the future earnings were expected to decrease, the value of an asset should decrease as well. The price and earnings components in the P/E ratio are rarely updated at the same time. Therefore, studying the earnings and price components separately could provide insight into the returns of the factor indices. Figures 14-18 present the EPS and P/E estimates for factor indices.

As can be observed from Figures 14 - 18, the P/E ratios of indices started to decrease before the analyst's EPS estimates at the beginning of the Covid-19 crisis. This indicates that the market reacted to the Covid-19 before the analyst earnings estimates were updated and the markets were already pricing in the decrease and uncertainty related to the future earnings. The earnings component in the P/E ratio was not reflecting this, and thus the P/E ratio decreased at the beginning of the crisis. This should not be seen as an indication of indices becoming fundamentally cheaper, as it is realistic to expect that the markets were already pricing in the decrease of future EPS, and thus the price reacted before the earnings estimates were updated. The P/E ratio for all factor indices started to rise at the end of March. Two main causes that should explain the increase of P/E multiple can be identified: First, the prices of factor indices started to rise at the end of March naturally raising the price component in the P/E ratio. The second contributor to the higher P/E ratio is that the 12-month earnings estimates decreased during the full sample period, thus raising the P/E ratio from the denominator side as well. For all factor indices, the P/E ratio ended being higher than at the beginning of the studied period. This should indicate that part of the returns of indices is based on the expansion of the P/E multiple, making investors pay more for future earnings, or that the earnings estimates are too pessimistic. Besides, investors are probably looking beyond the next 12 months' earnings estimates.

Figure 14 presents the EPS and P/E estimates for value factor indices. The EPS estimates for the CRSP US Large Cap Value Index decreased the least, whereas for the MSCI Europe Enhanced Value Index, the estimates decreased the most. A closer look reveals that there seems to be a correlation between the performance of an index and the EPS estimates. A higher decrease in estimated EPS seems to contribute to a weaker performance in terms of price. In the U.S market, the Russell 1000 Value Index (-16.53%) underperformed compared to the CRSP US Large Cap Value Index (-15.82 %) and S&P 500® Value Index (-15.81 %), which on the other hand, have relatively similar EPS estimates and performance. The highest decrease in EPS is estimated for the MSCI Europe Enhanced Value Index (-19.78 %), which performed the weakest in terms of returns.

The underperformance of the Russell 1000 Value Index and a relatively high decrease in EPS estimates should be partly explained by the equity universe, which includes smaller stocks for the Russell 1000 Value Index compared to the CRSP US Large Cap Value Index and S&P 500® Value Index. The P/E ratios of value factor indices behaved in a relatively similar manner during the studied time period, and there were no clear signs of expansion or contraction of P/E multiples between the indices. In absolute terms, the trend in forward-looking P/E ratios was clearly rising.

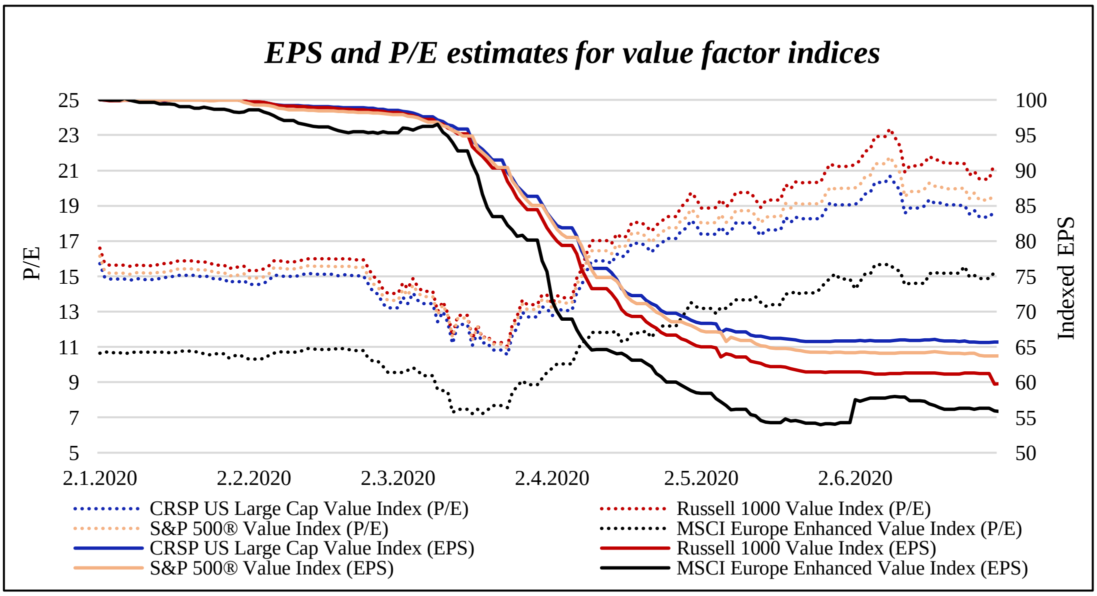

Figure 14. *EPS and P/E of value factor indices*

Figure 15 presents the EPS and P/E estimates for size factor indices. There are relatively large differences in the indexed EPS estimates, however, the EPS estimates do not fully correlate with the performance of factor indices due to the asymmetrical expansion of P/E multiples. The EPS estimates decreased most for the Russell 2000 Index (-12.91 %), but the Russell 2000 Index also had the highest increase in the P/E ratio that overcompensated the decrease in estimated EPS. Due to the greatest increase in P/E multiple, the return of the Russell 2000 Index was higher than the return of the S&P SmallCap 600® Index (-17.85%), which was the worst-performing size factor index. The S&P SmallCap 600® Index had a 67% decrease in trailing the next 12-month EPS and the second-largest P/E multiple expansion after the Russell 2000 Index. The best performing size factor index was the CRSP US SmallCap Index (-11.52 %). However, the MSCI EMU Small Cap Index (-14.06 %) had the smallest multiple expansion and decrease in estimated EPS.

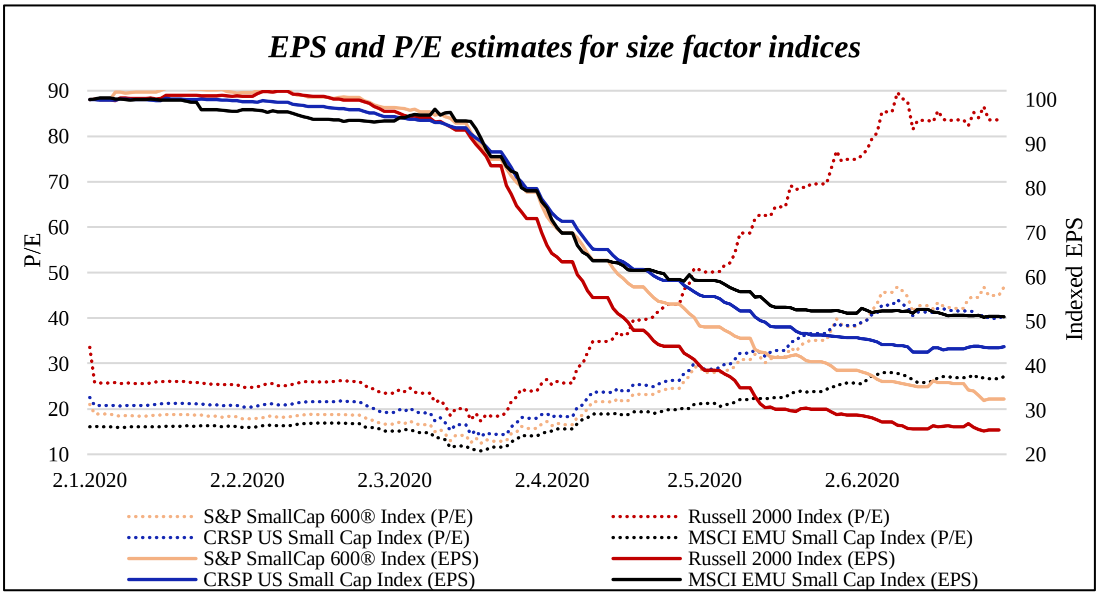

Figure 15. *EPS and P/E of size factor indices*

Figure 16 presents the EPS and P/E estimates for momentum factor indices. For the DW Technical Leaders Index (4.47 %), there were no EPS or P/E data available, and thus this index is excluded from the figure. Overall, it can be observed that the EPS estimates for momentum factor indices decreased the least among the studied factor indices. For the MSCI USA Momentum Index (4.90 %), the decrease in EPS estimates was approximately 10 percent, whereas for the MSCI Europe Momentum Index (-0.58 %), the decrease was 29 percent. For the JP Morgan US Momentum Factor Index (1.65 %), the decrease was approximately 23 percent. The MSCI USA Momentum Index outperformed other momentum indices and had the lowest decrease in terms of EPS estimates. It also had the lowest rise in forward-looking P/E from 25 to 29. The return of the JP Morgan US Momentum factor Index can be explained partly by its relatively high P/E multiple expansion from 25 to 32. The EPS estimates for the MSCI Europe Momentum Index decreased the most, but this was partially off-setted by the P/E multiple expansion from 20 to 27, despite of which, the MSCI Europe Momentum Index underperformed (-0.58%) relative to its U.S. counterparts.

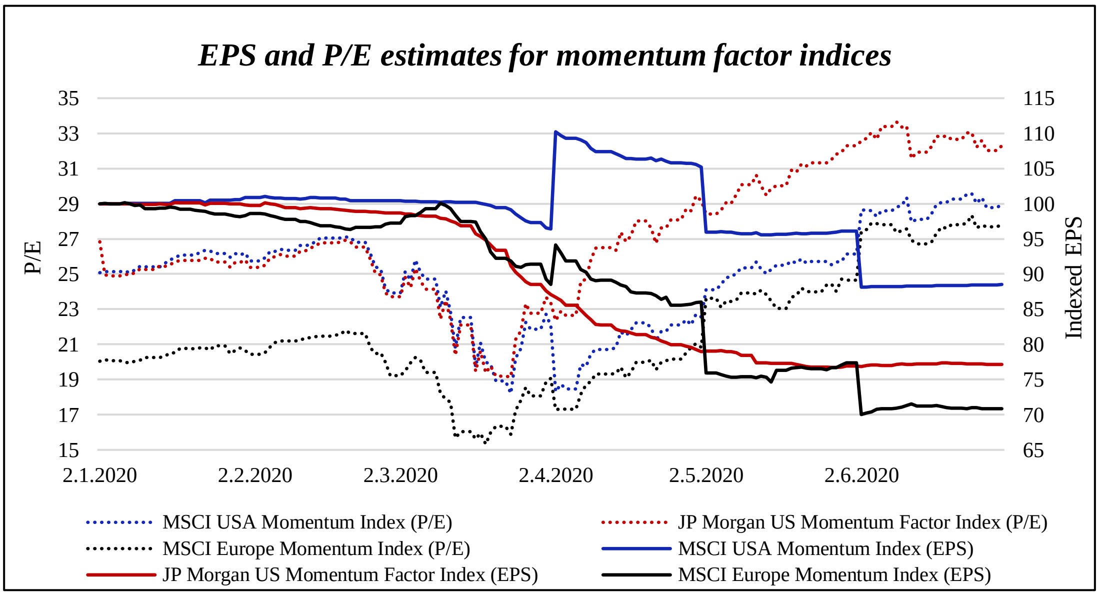

Figure 16. *EPS and P/E of momentum factor indices*

The development of the estimated EPS and P/E for ESG indices is shown in Figure 17. No data was available for the MSCI USA Extended ESG Leaders Index (-2.52 %), and thus it is excluded from the figure. The MSCI Europe SRI Select Reduced Fossil Fuel Index (-7.79 %) is quoted in euros since dollar data was not available. The MSCI USA Extended ESG Focus (-1.88 %) and the MSCI USA ESG Leaders (-2.52 %) U.S. indices performed very similarly in terms of EPS and P/E estimates, however, the MSCI USA Extended ESG Focus Index had a marginally higher P/E expansion that explains the edge in performance. The MSCI Europe SRI Select Reduced Fossil Fuel Index performed the worst (-7.79%), which is explained by the highest decrease in estimated EPS and lowest multiple expansion.

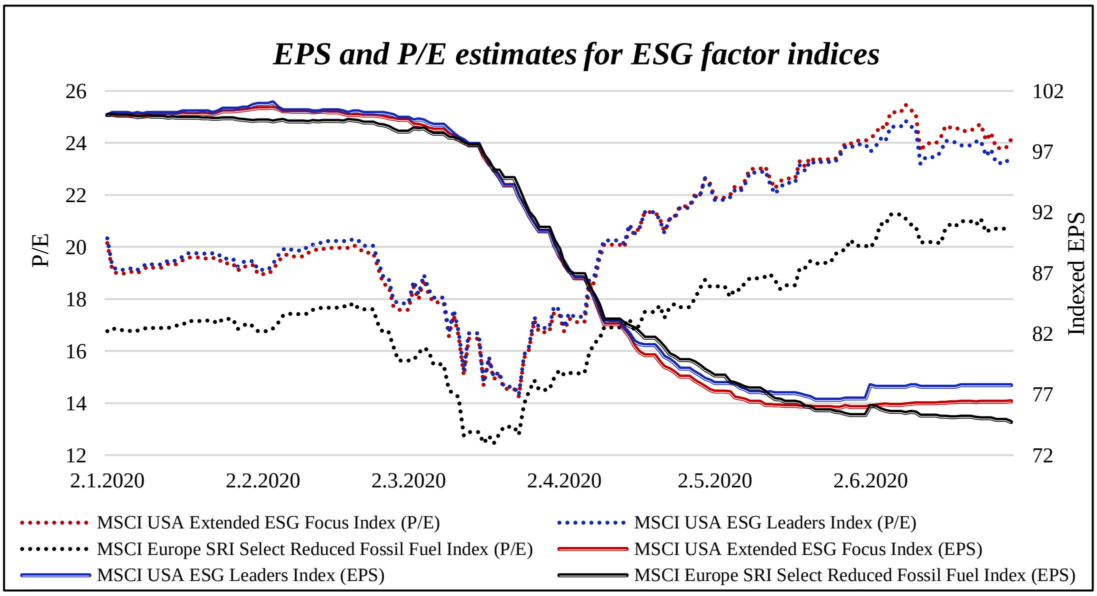

Figure 17. *EPS and P/E of ESG factor indices*

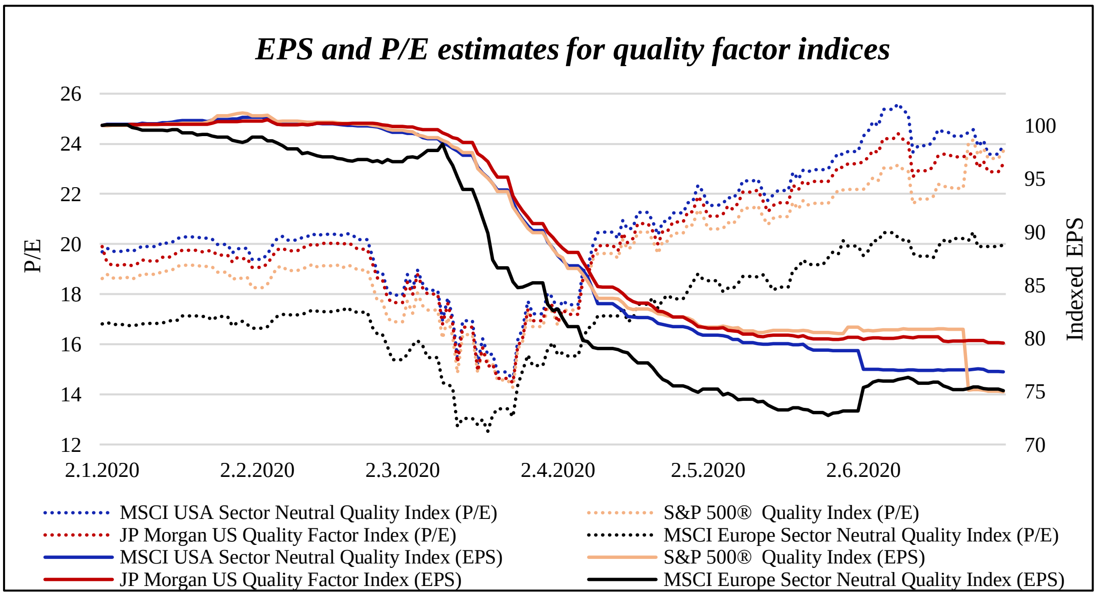

Figure 18. *EPS and P/E of quality factor indices*

Figure 18 illustrates the development of EPS estimates and the P/E ratio for quality factor indices. The EPS estimates for the MSCI Europe Sector Neutral Quality Index (-9.57 %) and the S&P 500® Quality Index (-2.85 %) decreased the most. The S&P 500® Quality Index had the highest multiple expansion that partly offset the decrease in EPS estimates. The JP Morgan US Quality Factor Index (-2.77 %) had the highest return and the lowest decrease in terms of estimated EPS. The MSCI USA Sector Neutral Quality Index (-4.90 %) had the lowest return of the U.S. indices, which is due to the relatively high decrease in EPS and relatively small expansion in terms of price to earnings multiple.

In a conclusion, there is a strong relationship between the estimated EPS and the returns of indices. The momentum factor was the least affected in terms of a decrease in earnings estimates, whereas the size and value factors were the most affected and had the lowest price returns. All indices had expansion in P/E multiples, but especially in the size factor category, most of the returns are explained by the expansion of P/E multiples. European indices had the highest decrease in EPS estimates in all factor categories except in size, where the EPS estimates decreased the least. In the ESG factor category, the differences between indices are very minimal both in terms of EPS, P/E, and total returns. When studying the development of the P/E ratio and EPS estimates, it can be seen that the price reacted before the EPS estimates were updated.

4.4 Correlation

The correlation of factor indices is studied to analyze the diversification benefits during the Covid-19 crisis. The results are analyzed by utilizing a correlation matrix where the bottom half presents the correlation of indices during the Covid-19 crisis, and the upper half presents the correlation before the Covid-19 pandemic. The correlation before the pandemic is calculated by utilizing daily observations one year before the crisis, 2019. The data before the crisis is analyzed to make the results comparable with a normal market environment. During the crisis, daily observations are utilized from the studied 6-month time period. The correlation coefficients presented in Table 16 are harmonized in order to enable the comparability of time-periods with different lengths, consistent with Pätäri (2011) and Pätäri, Ahmed, John, and Karell (2019). The harmonization is conducted for the crisis period based on the significance levels of t-statistics. This is accomplished by fetching the harmonized correlation coefficient with the same significance level but with higher degrees of freedom due to the larger sample before the pandemic. Thus, the harmonized correlation coefficients decrease during the crisis compared to unharmonized data enabling comparability between the samples. All the coefficients in Table 16 are highly statistically significant. In general, it can be observed that the correlations between the factors were relatively high across factor indices before the crisis, especially among the U.S. indices. The average correlation coefficient was 0.82 before the crisis and 0.76 during the crisis period. This finding is consistent with the results of Brière and Szafarz (2017a) and Centineo and

Centineo (2017), who identified relatively high correlations among factors during the past decades.

The size factor is the least correlated with other factors when the correlations are analyzed before the crisis. The correlation of size factor indices generally varies between 0.5 – 0.9 when compared to other factor indices. In addition, value and momentum have a relatively low correlation, which is due to the strong performance of momentum and poor performance of value. By contrast, ESG and quality factor indices are highly correlated with each other, which is explained by the relatively similar composition of constituents included in these indices. Geographically, it can be detected that the correlation between U.S. indices is strong, whereas the correlation between U.S. and European indices is lower. The average correlation between the U.S. indices is 0.9, between the U.S. and European indices 0.65, and between European indices, it is approximately 0.87.

By analyzing the period during the crisis, it can be observed that generally, the correlations decreased between factors. The size factor is still the least correlated with other factors, and the correlation varies typically between 0.5 – 0.8 compared to other factors. The value and momentum factors still have a relatively low correlation that is explained by the disunity in performance. Similar results were obtained by Cakici et al. (2013) and Asness et al. (2013), who provided evidence that there are diversification benefits to be gained between momentum and value factors. Geographically the same phenomena can be identified when comparing the correlation between the market areas. The average correlation between the U.S. indices is 0.86, between the U.S. and European indices 0.55, and between European indices, it is approximately 0.83. The correlations between factors were relatively high but decreased during the crisis due to divergence in performance. This finding is inconsistent with the results of Arnott et al. (2019), who stated that during periods of market tension, most diversification benefits among factors can disappear as the factors begin to behave in unison. However, Centineo and Centineo (2017) found that the diversification benefits among factors are pronounced during the bear market, which supports the findings of this thesis. As a conclusion, diversification benefits are relatively small among factors both during and before the crisis. Overall, the least correlated factor before and during the crisis is the size factor, in addition, the momentum and value have a relatively low correlation.

Table 16. *Correlation matrix*

Index	1. CRSP	2. Russell	3. S&P	4. MSCI	5. S&P	6. Russell	7. CRSP	8. MSCI	9. MSCI	10. DW	11. JP	12. MSCI	13. MSCI	14. MSCI	15. MSCI	16. MSCI	17. MSCI	18. S&P	19. JP	20. MSCI
1. CRSP US Large Cap Value	**1,000**	0,995	0,985	0,733	0,868	0,873	0,905	0,684	0,819	0,793	0,864	0,618	0,960	0,951	0,951	0,678	0,944	0,923	0,942	0,656
2. Russell 1000 Value	0,956	**1,000**	0,986	0,731	0,886	0,891	0,924	0,685	0,815	0,801	0,867	0,610	0,961	0,951	0,951	0,672	0,947	0,922	0,943	0,651
3. S&P 500 Value	0,982	0,965	**1,000**	0,744	0,889	0,893	0,923	0,703	0,808	0,798	0,869	0,604	0,969	0,951	0,951	0,672	0,955	0,936	0,943	0,651
4. MSCI Europe Enhanced Value	0,595	0,609	0,599	**1,000**	0,656	0,651	0,672	0,877	0,553	0,557	0,613	0,748	0,721	0,705	0,705	0,884	0,712	0,697	0,699	0,866
5. S&P SmallCap 600®	0,795	0,826	0,804	0,617	**1,000**	0,988	0,970	0,628	0,673	0,719	0,774	0,488	0,860	0,837	0,837	0,557	0,843	0,820	0,828	0,528
6. Russell 2000	0,801	0,831	0,810	0,611	0,934	**1,000**	0,984	0,634	0,711	0,756	0,809	0,504	0,879	0,858	0,858	0,565	0,861	0,840	0,850	0,538
7. CRSP US Small Cap	0,835	0,869	0,846	0,621	0,898	0,932	**1,000**	0,665	0,780	0,831	0,873	0,556	0,922	0,907	0,907	0,606	0,908	0,888	0,903	0,583
8. MSCI EMU Small Cap	0,547	0,563	0,551	0,831	0,569	0,568	0,584	**1,000**	0,591	0,600	0,651	0,773	0,714	0,706	0,705	0,868	0,704	0,705	0,695	0,827
9. MSCI USA Momentum	0,793	0,776	0,791	0,503	0,652	0,690	0,726	0,469	**1,000**	0,935	0,961	0,658	0,905	0,920	0,920	0,631	0,904	0,917	0,931	0,623
10. Dorsey Wright Technical Leaders	0,809	0,800	0,811	0,528	0,695	0,740	0,773	0,498	0,899	**1,000**	0,966	0,639	0,886	0,904	0,904	0,616	0,888	0,892	0,918	0,605
11. JP Morgan US Momentum Factor	0,860	0,859	0,865	0,570	0,749	0,786	0,826	0,538	0,879	0,917	**1,000**	0,662	0,949	0,957	0,957	0,652	0,943	0,951	0,965	0,640
12. MSCI Europe Momentum	0,534	0,542	0,536	0,765	0,526	0,542	0,555	0,742	0,516	0,536	0,549	**1,000**	0,658	0,672	0,671	0,922	0,667	0,675	0,686	0,937
13. MSCI USA Extended ESG Focus	0,903	0,890	0,904	0,572	0,763	0,787	0,821	0,534	0,860	0,879	0,928	0,538	**1,000**	0,992	0,992	0,693	0,988	0,979	0,987	0,677
14. MSCI USA ESG Leaders	0,900	0,889	0,901	0,572	0,761	0,787	0,822	0,534	0,864	0,884	0,933	0,540	0,973	**1,000**	1,000	0,698	0,985	0,975	0,990	0,680
15. MSCI USA Extended ESG Leaders	0,900	0,889	0,901	0,572	0,761	0,787	0,822	0,534	0,864	0,884	0,933	0,540	0,973	1,000	**1,000**	0,698	0,985	0,975	0,990	0,680
16. MSCI Europe SRI Select Reduced Fossil	0,561	0,571	0,563	0,851	0,564	0,570	0,581	0,822	0,505	0,529	0,557	0,868	0,553	0,554	0,554	**1,000**	0,690	0,692	0,701	0,974
17. MSCI USA Sector Neutral Quality	0,907	0,889	0,905	0,574	0,753	0,773	0,809	0,531	0,850	0,862	0,903	0,537	0,948	0,949	0,949	0,553	**1,000**	0,980	0,987	0,677
18. S&P 500® Quality	0,882	0,855	0,876	0,545	0,711	0,730	0,764	0,506	0,855	0,853	0,879	0,515	0,922	0,921	0,921	0,529	0,937	**1,000**	0,983	0,681
19. JP Morgan US Quality Factor	0,910	0,893	0,909	0,570	0,760	0,783	0,817	0,530	0,863	0,879	0,925	0,536	0,966	0,966	0,966	0,551	0,953	0,933	**1,000**	0,689
20. MSCI Europe Sector Neutral Quality	0,562	0,572	0,564	0,829	0,558	0,567	0,582	0,790	0,514	0,536	0,560	0,882	0,554	0,555	0,555	0,918	0,555	0,529	0,551	**1,000**

* The upper half of the matrix represents the correlations of factor indices before the Covid-19 crisis covering the year 2019. The lower half represents the correlations of factor indices during the Covid-19 covering the first six months from the beginning of 2020.

4.5 Performance of pure factor portfolios

The performance of pure factor portfolios is analyzed in this sub-section. As a reminder, pure factor portfolios are constructed to achieve purer factor tilt for the desired factor without any restrictions. Long-only portfolios consist of 1/3 of the highest factor exposure stocks, whereas on the long-short portfolios 1/3 of stocks with the least factor characteristics are also shorted. As of total, 32 factor portfolios are constructed, where half of the portfolios are market-weighted portfolios, and the other half are equally-weighted portfolios. Long-only and long-short strategies are applied for both market- and equally-weighted portfolios. The returns presented in this sub-section are total returns for the full sample period and no rebalancing is conducted. The equity universe for the US factor portfolios is the S&P 500 index and Stoxx 600 for the European portfolios from which the factor portfolios are structured by utilizing the R-programming language. The returns reflect theoretical returns since transaction costs are not taken into account to make the results comparable with the studied factor indices. In Appendix 5, the performance is graphically presented.

The results for equally-weighted pure factor portfolios can be seen below in Table 17. The average returns of the studied factor indices for the full sample period are included in the table to make the result comparable with pure factor portfolios. As can be observed from Table 17, long-short portfolios generally outperformed the long-only portfolios, except in the value category in the U.S. market. In the value category, growth stocks that have high P/E and P/B multiples clearly outperformed value stocks (low P/E, P/B) and returned a positive return when the full sample period is considered. Shorting of growth stocks increased the negative return of long-short portfolios, although the difference in returns between long-short and long-only was only 0.34%. In other factor categories, the long-short portfolios outperformed long-only portfolios with a margin between 0.99% - 16.71%.

Equally-weighted long-only portfolios generally underperformed the studied factor indices. Merely, the size and quality factors in Europe generated excess returns compared to the studied indices. The performance of the size factor should be explained by the strong returns of small market capitalization companies in Europe, and the equally-weighted methodology allocates higher weight on these stocks. Pure factors performed in similar order value performing the worst followed by size, quality, and momentum performing the strongest when the returns of factor categories are compared between equally-weighted indices and studied factor indices. Interestingly the ordinal performance can be observed in both markets and both long-only and long-short portfolios. Long-short portfolios outperformed studied factor indices in all categories except in the value factor category. It can be concluded that overall, long-short pure factor portfolios generated superior returns compared to studied factor indices. This is logical since during a market crash, shorting generates positive returns, however, it is very difficult to time the market crashes before these occur.

Table 17. *The performance of equally-weighted pure factor portfolios*

	Equally-weighted			Studied factor indices	Long-only	Long-short
Factor	Long-only	Long-short	Difference	Average	Excess return	Excess return
Value U.S.	-22,89 %	-23,23 %	0,34 %	-16,05 %	-6,84 %	-7,18 %
Value Europe	-21,30 %	-20,30 %	-0,99 %	-19,78 %	-1,52 %	-0,52 %
Size U.S.	-14,99 %	-8,52 %	-6,47 %	-14,09 %	-0,90 %	5,57 %
Size Europe	-7,83 %	5,97 %	-13,80 %	-14,06 %	6,23 %	20,03 %
Momentum U.S.	-4,56 %	12,15 %	-16,71 %	3,67 %	-8,23 %	8,48 %
Momentum Europe	-3,02 %	13,03 %	-16,05 %	-0,58 %	-2,44 %	13,61 %
Quality U.S.	-5,35 %	8,50 %	-13,85 %	-3,51 %	-1,84 %	12,01 %
Quality Europe	-6,30 %	8,07 %	-14,38 %	-9,57 %	3,27 %	17,64 %

* Difference = The performance of long-only – the performance of long-short
Excess return = The performance of long-only/long-short – the performance of average return of studied factor indices

Table 18 presents the performance of market capitalization-weighted long-only and long-short pure factor portfolios and compares it to the average returns of studied factor indices. The same observation can be done as with equally-weighted portfolios when analyzing the difference in returns between long-only and long-short strategies. Long-short portfolios outperformed long-only counterparts except in the value factor category in the U.S. market. This was due to the strong performance of high P/E and P/B stocks that generated positive returns and shorting these stocks generated extra losses.

The market capitalization-weighted long-only pure factor portfolios generally generated inferior returns compared to studied indices, however, the quality pure factor portfolios produced high excess returns in both markets. This can be explained by the more favorable sector mix of the quality pure factor portfolios (Appendix 6). In Europe, the pure factor portfolio produced excess returns in the size factor category. Pure factor portfolio has fewer stocks in the portfolio (pure factor portfolio 198 vs. 432), and thus the average market capitalization of a stock is smaller as well. Small-cap stocks outperformed in Europe, and due to the higher tilt on small-capitalization stocks, the return of pure size factor portfolio was higher as well.

Table 18. *The performance of market capitalization-weighted pure factor portfolios*

	Market cap-weighted			**Studied factor indices**	Long-only	Long-short
Factor	Long-only	Long-short	Difference	Average	Excess return	Excess return
Value U.S.	-21,69 %	-31,09 %	9,41 %	-16,05 %	-5,64 %	-15,04 %
Value Europe	-25,84 %	-21,90 %	-3,94 %	-19,78 %	-6,06 %	-2,12 %
Size U.S.	-14,49 %	-13,74 %	-0,76 %	-14,09 %	-0,40 %	0,35 %
Size Europe	-9,95 %	2,51 %	-12,46 %	-14,06 %	4,11 %	16,57 %
Momentum U.S.	2,45 %	17,77 %	-15,32 %	3,67 %	-1,22 %	14,10 %
Momentum Europe	-6,94 %	12,56 %	-19,50 %	-0,58 %	-6,36 %	13,14 %
Quality U.S.	2,51 %	4,82 %	-2,31 %	-3,51 %	6,02 %	8,33 %
Quality Europe	-5,80 %	12,49 %	-18,30 %	-9,57 %	3,77 %	22,06 %

* Difference = The performance of long-only – the performance of long-short
Excess return = The performance of long-only/long-short – the performance of average return of studied factor indices

Table 19 presents the performance between market capitalization-weighted and equally-weighted portfolios. In long-only factor portfolio comparisons, capitalization-weighted portfolios outperformed equally-weighted portfolios in all categories in the U.S. market area and the quality factor category in Europe. These findings are inconsistent with various studies (e.g., Plyakha et al. 2012; Bolognesi et al. 2013; Blitz 2016; MSCI 2020c) that advocate equally-weighted indices over market capitalization indices. However, the studies of Plyakha et al. (2012), Bolognesi et al. (2013), Blitz (2016), and MSCI (2020c) focus on the long-term returns, and thus the findings may not be generalized for short time periods or the periods of high market volatility. By contrast, equally-weighted long-only portfolios outperformed in the European markets. The strong performance of equally-weighted portfolios is due to the outperformance of small-capitalization stocks compared to large-capitalization stocks in the European market. On the other hand, large-cap stocks outperformed small-caps in the U.S. market. Equally-weighted portfolios allocate more weight on small-cap stocks, whereas value-weighted portfolios do it proportionally to the market capitalization. Therefore, large-cap stocks have a higher weight in value-weighted portfolios. In long-short portfolio comparisons, equally-weighted pure factor portfolios outperformed their value-weighted counterparts in all factor categories, except in the momentum category in the U.S. and quality in Europe. This is a relatively surprising finding since equally-weighted long-only portfolios underperformed against value-weighted portfolios. Therefore, the excess returns of equally-weighted portfolios must have stemmed from the short leg of portfolios.

Table 19. *The performance of value- and equally-weighted portfolios*

	Market cap-weighted		**Equally-weighted**		Long-only	Long-short
Factor	Long-only	Long-short	Long-only	Long-short	Difference	Difference
Value U.S.	-21,69 %	-31,09 %	-22,89 %	-23,23 %	1,20 %	-7,87 %
Value Europe	-25,84 %	-21,90 %	-21,30 %	-20,30 %	-4,54 %	-1,60 %
Size U.S.	-14,49 %	-13,74 %	-14,99 %	-8,52 %	0,49 %	-5,21 %
Size Europe	-9,95 %	2,51 %	-7,83 %	5,97 %	-2,12 %	-3,46 %
Momentum U.S.	2,45 %	17,77 %	-4,56 %	12,15 %	7,01 %	5,63 %
Momentum Europe	-6,94 %	12,56 %	-3,02 %	13,03 %	-3,92 %	-0,48 %
Quality U.S.	2,51 %	4,82 %	-5,35 %	8,50 %	7,85 %	-3,68 %
Quality Europe	-5,80 %	12,49 %	-6,30 %	8,07 %	0,50 %	4,42 %

* Difference = Market cap-weighted long-only/long-short – equally-weighted long-only/long-short.

Generally, the results indicate that the returns of studied factor indices are better than the returns of long-only pure factor portfolios. Based on the literature review, factor investing is often considered to be inherently riskier (e.g., Fama 1970; Bender et al. 2013; Ang 2014, 444), thus the excess returns of factor investing should be explained by the higher risk, especially with value and size factors. The objective of pure factor portfolios is to have as pure factor tilt as achievable, without taking into account any restrictions or adjustments for the free-float. The higher factor tilt of pure factor portfolios should therefore make the portfolio even riskier and lead to poorer performance during market crashes, which the findings of this study do support. Long-short pure factor portfolios provided superior returns in almost every aspect, however, this should not come as a surprise. Shorting of stocks during market crashes should be profitable to begin with. Nevertheless, according to Ilmanen and Kizer (2012) and Blitz (2016), the benefits of factor investing on a longer time horizon should be greater through long-short positions since it captures the pure factor premiums instead of assets premiums. Also, it has a lower correlation among asset class premiums compared to the long-only strategy. In practice, long-short strategies are rarely practiced due to the cost and complications related to implementing this strategy.

5. CONCLUSION AND DISCUSSION

This thesis examined the performance of factor investing during the Covid-19 crisis from the beginning of 2020, covering the first six months of the crisis. Crises occur irregularly, and thus every new crisis offers the possibility to study the performance of factor investing during unordinary market environments. As the Covid-19 crisis is a relatively new phenomenon, the performance of factor investing during this pandemic is not extensively studied in academia to the best of my knowledge. Besides, there is only a handful of academic studies regarding the performance of factor investing during times of crisis. This underlines the novelty of the subject and the distinct research gap which this study is endeavoring to fulfill by discussing and answering the research questions expressed in the introduction section:

Question 1. *How factor indices and ETFs performed during the Covid-19 crisis?*

According to the hypotheses formed from academia, the value factor should underperform the market index during the Covid-19 (e.g., Chen and Zhang 1998; Zhang 2005; Winkelmann et al. 2013), whereas the size factor should underperform during the bear market but rebound faster during the recovery period (e.g., Arshanapalli and Nelson 2007; Switzer 2010). The momentum factor is expected to underperform the market index, especially during the recovery period (e.g., Daniel and Moskowitz 2016; Cheema and Nartea 2017), while ESG (e.g., Nofsinger and Varma 2014; Lins et al. 2017) and quality (George 2002; Asness et al. 2019) factors, should outperform the market index, especially during the bear market. The factors performed relatively in line with these hypotheses, except the momentum factor that produced higher returns in all periods. However, this could be explained by the unordinary nature of the crisis. In addition, the ESG and quality factors were expected to be more defensive during the crisis, especially in the bear market, but they performed relatively parallel with the market indices.

Table 20 summarizes the average returns of the U.S. factor indices as well as the returns of European factor indices. The European indices lagged the U.S. counterparts thoroughly, especially during the recovery phase. The overall sector performance was notably stronger in the U.S. compared to Europe. In addition, large-cap stocks outperformed small-cap stocks in the U.S., whereas the reverse held in Europe. The factor indices are value-weighted indices, and therefore, large market capitalization stocks contribute more to the total returns of factor indices.

The value factor indices (-16.05%/-19.78%, US/EU) had the poorest performance on average, followed by size (-14.09%/-14.06%), quality (-3.51%/-9.57%), ESG (-2.31%/-7.79%), and momentum factor indices (3.67%/-0.58%) when the performance of factors is considered during the full sample period. Momentum, ESG, and quality factor indices were able to produce excess returns compared to the benchmark indices, whereas value and size were outperformed by market indices. During the bear market, the weakest performance in the U.S. was recorded for the size factor, decreasing more than 40%, on average, whereas in Europe, the value factor turned out to be the worst performer (-39.52%). The quality factor (-32.42%) was the strongest performer in the U.S. and the momentum factor (-29.34%) in Europe during the bear market on average. During the recovery period, the strongest performers were momentum (32.39%/22.28%) and size factor (31.77%/25.00%) indices in both market areas.

Table 20. *Average returns of factor indices*

Factor Index	Full Period	Bear	Recovery
The U.S. Market	Absolute return		
Value	-16,05 %	-37,09 %	20,95 %
Size	-14,09 %	-41,38 %	31,77 %
Momentum	3,67 %	-33,86 %	32,39 %
ESG	-2,31 %	-33,93 %	28,00 %
Quality	-3,51 %	-32,42 %	26,35 %
S&P 500 Index	-3,90 %	-33,54 %	27,34 %
European Market			
Value	-19,78 %	-39,52 %	20,39 %
Size	-14,06 %	-37,67 %	25,00 %
Momentum	-0,58 %	-29,34 %	22,28 %
ESG	-7,79 %	-31,62 %	20,11 %
Quality	-9,57 %	-32,44 %	19,99 %
Stoxx 600 Index	-12,59 %	-34,54 %	19,94 %

Generally, the poor performance of value and size factor indices was somewhat expected. According to the literature review, these factors are inherently riskier, and thus the factor premiums are a reward for investing in stocks that are often under financial distress (e.g., Fama and French 1993; Winkelmann et al. 2013). The strong performance of the momentum factor was not expected based on the literature review. Favorable sector allocation of momentum indices contributes strongly to the overall returns of the factor. However, the differences in mean returns of the samples were not statistically significant, according to Welch's t-test.

The actual return that investors would achieve by investing in factor ETFs differs from the theoretical returns commonly studied in academia. All factor ETFs underperformed their benchmark factor indices, but the differences in returns were relatively small, on average -0.19% varying from 0.00% to -0.68% during the full sample period. Generally, European ETFs lagged more their benchmark indices compared to the U.S. counterparts. The performance of ETFs is affected by the tracking error, which decreased the returns received by the investor. Tracking error was highest in the size factor category and lowest in the value factor category. Generally, the tracking error of the European ETFs was higher when compared to the U.S. counterparts. This study provided evidence that high tracking error is affected by the expense ratio, the AUM of ETFs, as well as the volatility of the daily returns. This observation is consistent with the findings of Chu (2011), Singh and Kaur (2016), and Tsalikis and Papadopoulos (2019).

Sub-Question 1.1. *What elements explain the differences in performance?*

The methodology of indices, the sector performance, and allocations, as well as relative valuation metrics, were utilized to explain the performance of factors. The performance of factor indices and ETFs is principally based on the performance of constituents included in the index. The constituents and the sector allocations are selected in accordance with the methodology of indices, which differs between index providers and indices. The main difference between the methodologies of indices is the number of variables and different variables used in the factor classification. In addition, the number of constituents, sector neutrality restrictions, the security weighting methodology, as well as rebalancing cycles all affected the final constituents and the total performance of an index.

In addition to the methodology of indices, this thesis quantitatively provided evidence that the sector performance and allocations of the underlying ETF greatly contribute to the total returns in all factors except in size. Sector contribution analysis revealed that the largest absolute negative sector contribution to the returns of ETFs was caused by financials, energy, and industrials. The largest positive sector contribution was achieved from information technology and healthcare. The results of the sector contribution relative to the benchmark revealed that the U.S. value ETFs had the highest weight on energy and financial sectors, which underperformed during the Covid-19. In addition, the U.S. value ETFs had the underweight on information technology that outperformed during the crisis, and thus the combination of these sector bets resulted in the poor performance of the value factor. A similar pattern was observed in the size category, although less vigorously. ESG and quality ETFs were relatively neutral, and no distinct sector bets were observed, thus resulting in a similar performance with benchmark indices. Momentum ETFs had the underweight on energy and financial sectors, thus resulting in a more favorable sector mix, which contributed positively to the total returns of momentum ETFs.

The relative valuation revealed that there is a clear relationship between the EPS estimates and the return of factor indices. The momentum factor was the least affected in terms of a decrease in EPS estimates, while the value and size factors were the most affected. In addition, the expansion of P/E multiple provided insights to explain the performance of factors. In the size factor category, most of the returns are explained by the P/E expansion, however, all indices had some sort of expansion in P/E multiple during the Covid-19.

Sub-Question 1.2. *How correlated the returns of factors were ex-ante and midst the Covid-19 crisis?*

The correlation coefficients between the factors were relatively high, on average, the coefficient was 0.82 before the crisis and 0.76 during the crisis period. This finding is consistent with the results of Brière and Szafarz (2017a) and Centineo and Centineo (2017), who identified relatively high correlations among factors during the past decades. The size factor was before and during the crisis, the least correlated with other factors with a coefficient of 0.5 – 0.9. In addition, the value and momentum factors had a relatively low correlation that was explained by the disunity in total returns.

The correlations were generally higher within the same market area than between the U.S. and European indices. The average correlation between the U.S. indices was 0.86 (before the crisis 0.9), between the U.S. and European indices 0.55 (0.65), and between European indices, it was approximately 0.83 (0.87) during the crisis. Overall, the correlations between factors were relatively high but decreased during the crisis due to the differential performance of factors. The decreased correlation between factors during the crisis period was consistent with the findings of Centineo and Centineo (2017). Based on the results, in general, the diversification benefits are relatively small among long-only factor indices in normal market environments and during a market crisis.

Question 2. *How the pure factor portfolios performed during the Covid-19?*

The summary of the results regarding the performance of pure factor portfolios is presented in Table 21. A total of 32 pure factor portfolios were formed by utilizing different methodologies to accomplish extensive results. Table 21 ease the reader to interpret these results.

Table 21. *Summary of the results*

	Market cap-weighted		**Equally-weighted**		**Studied factor indices**
Factor	Long-only	Long-short	Long-only	Long-short	Average
Value U.S.	-21,69 %	-31,09 %	-22,89 %	-23,23 %	-16,05 %
Value Europe	-25,84 %	-21,90 %	-21,30 %	-20,30 %	-19,78 %
Size U.S.	-14,49 %	-13,74 %	-14,99 %	-8,52 %	-14,09 %
Size Europe	-9,95 %	2,51 %	-7,83 %	5,97 %	-14,06 %
Momentum U.S.	2,45 %	17,77 %	-4,56 %	12,15 %	3,67 %
Momentum Europe	-6,94 %	12,56 %	-3,02 %	13,03 %	-0,58 %
Quality U.S.	2,51 %	4,82 %	-5,35 %	8,50 %	-3,51 %
Quality Europe	-5,80 %	12,49 %	-6,30 %	8,07 %	-9,57 %

❖ ***Market capitalization- vs. equally-weighted, the long-only strategy***

The capitalization-weighted portfolios outperformed the equally-weighted counterparts in all factor categories in the U.S. market when the performance is measured between long-only factor portfolios. The opposite results were observed in the European market area, where equally-weighted long-only pure factor portfolios outperformed their cap-weighted counterparts, except in the quality factor category. These results are explained by the opposite relative performance of small and large-capitalization companies in the U.S. and in Europe.

❖ ***Market capitalization- vs. equally-weighted, the long-short strategy***

Equally-weighted long-short portfolios outperformed their value-weighted counterparts in all factor categories, except in momentum in the U.S. and quality in Europe. Except the value factor in the U.S., all value- and equally-weighted long-short portfolios outperformed their long-only counterparts by a margin from 0.76% to 19.50%. The outperformance of the long-only value factor portfolio in the U.S. was due to the strong performance of growth stocks that generated positive returns and shorting these stocks on a long-short portfolio generated extra losses during the full sample period.

- ***Market capitalization- vs. equally-weighted vs. examined factor indices***

In general, both value- and equally-weighted long-only pure factor portfolios produced inferior returns compared to the examined factor indices. The equally- and value-weighted pure size and quality factor portfolios in Europe outperformed the comparable factor indices. In addition, the capitalization-weighted U.S. quality factor portfolio was also able to outperform its factor index counterparty. The outperformance of the equally-weighted size factor portfolio is explained by the strong performance of small-cap companies in Europe. Value-weighted pure quality factor portfolios outperformed due to more favorable sector allocation. Long-short pure factor portfolios outperformed the examined factor indices in all categories except in value. During a market crash, shorting usually generates positive returns, however, long-short strategies are rarely practiced due to the cost and complications of implementing this strategy.

Factor investing is often considered to be inherently riskier (e.g., Fama 1970; Bender et al. 2013; Ang 2014, 444). This study supports this hypothesis since higher and purer factor tilt of long-only pure factor portfolios increased the underperformance, thus indicating that factor premiums are compensation for taking a higher risk.

5.1 Contribution to academia

The contribution of this research is to advance the academic debate on the performance of factor investing during a time of crisis. Most academic studies on factor investing have highlighted the persistent long-term excess returns of factor investing (see, e.g., Banz 1981; Fama and French 1993; Jegadeesh and Titman 1993; Lakonishok et al. 1994). There is, however, a relatively low number of studies related to the performance of factor investing during a time of crisis. To the best of my knowledge, there are no studies related to the performance of academically-grounded factors during the Covid-19 pandemic. As a non-traditional and academically less examined factor, the performance of the ESG factor is studied, contributing to academia in this regard as well.

Generally, in academia, factor investing is studied in isolation without taking into account the practical aspects and costs involved in the process. According to the literature review, when the practical aspects are considered, the performance of factor investing is less promising (see, e.g., Malkiel 2014; Jacobs and Levy 2014; Arnott et al. 2019). This thesis studied the performance of existing factor ETFs products, therefore considering the practical aspects as well. The results revealed that most factor ETFs produced higher returns than the market indices even when the costs are considered. Many academic studies (e.g., Chu 2011, Singh and Kaur 2016, and Tsalikis and Papadopoulos 2019) have recognized the positive correlation between the tracking error and the AUM of ETF. The results of this study support finding and thus advanced the academic debate from this point as well. The academic evidence related to the correlation and diversification benefits of factors is contradictory. This study provided evidence that diversification benefits are relatively small among long-only factor portfolios both in crisis and normal market conditions.

The study formed academic pure factor portfolios as well and demonstrated how a purer factor exposure implies a higher risk and thus lower returns during a crisis. Factor investing can be practiced either by applying long-short or long-only strategies. Some studies advocate a long-short strategy over a long-only approach (e.g., Brière and Szafarz 2017b), whereas other studies prefer a long-only strategy (e.g., Blitz 2012). This thesis analyzed the performance of both strategies by applying both value- and equally-weighted portfolio-formation methodologies. In addition to the presented contributions to academia, sector return contribution analysis was conducted to illustrate the contribution of sector performance to the total returns of ETFs.

5.2 Research criticality and limitations

The Covid-19 is still an ongoing and evolving pandemic, and this research focuses and covers only the first 6 months of the Covid-19 crisis. This might be the largest limitation of the research that needs to be addressed. The second limitation concerns the practical aspects of the long-short implementation strategy during the crisis. The short-selling of stocks was banned during the crisis in various markets, and therefore, the implementation of a long-short strategy was practically infeasible, and the results reflect only theoretical returns (Cuervo and Stobo 2020; Remondini and Katz 2020; Barzic, Jones, Blenkinsop, and Knolle 2020; ESMA 2020). It should be noted that every crisis is different and occur for different reasons. The performance of factor indices might be different during the next crisis. Nevertheless, every crisis offers the possibility to analyze the performance of factors from which the future hypotheses can be drawn. However, one should remember that past performance is no guarantee of future performance.

5.3 Suggestions for further research

The most evident extension possibilities are associated with diverging the main variables applied in the study. Future research could focus on studying the Covid-19 crisis by applying different factors, ETFs, or factor indices. This study focused on developed markets, but a similar study could be replicated in developing markets as well. Suggestion for further research includes extending the time period beyond the first six months of the crisis by applying an even broader time period. Another contingent research suggestion could be to study how the studied factor indices have performed during previous crises and compare the performance to the Covid-19 crisis to see whether the results in this crisis can be further generalized. However, this is limited by the fact that most of the examined factor indices have been established relatively late. In addition, a prospective research objective could be to study the performance of pure factor portfolios during a longer time period by applying the methodology of pure factor portfolios. Due to their higher factor tilt, presumably making the portfolios riskier, most of the pure factor portfolios underperformed during the market crisis compared to the examined factor indices. However, due to the factors' purer nature, the excess returns could be reaped on a longer time horizon. As a conclusion, factor investing is a very interesting investment strategy, which is why I encourage others to explore this subject more.

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APPENDICES

Appendix 1. Factor ETFs by AUM

Value Factor – The United States (Usd)

NAME	ETF AUM
Fidelity US Value Currency Neutral Index ETF Series L Trust Units	2 405 140
ClearBridge Focus Value ETF	2 618 168
Principal Contrarian Value Index ETF	3 370 013
BMO MSCI USA Value Index ETF	5 025 369
iShares Factors US Value Style ETF	6 040 080
Fidelity US Value Index ETF Series L Trust Units	6 101 350
Lyxor Russell 1000 Value UCITS ETF	6 462 560
CI First Asset Morningstar US Value Index ETF	9 411 076
CI First Asset Morningstar US Value Index ETF	9 935 842
iShares Focused Value Factor ETF	19 962 420
SPDR S&P 1500 Value Tilt ETF	20 383 660
SPDR MFS Systematic Value Equity ETF	20 671 680
Roundhill Acquirers Deep Value ETF	21 310 600
Direxion Russell 1000 Value Over Growth ETF	21 394 840
iShares Edge MSCI USA Value Factor UCITS ETF	22 879 150
AdvisorShares DoubleLine Value Equity ETF	41 488 560
JPMorgan U.S. Value Factor ETF	60 588 000
Smartshares US Large Value ETF	68 447 490
Invesco S&P 500 Enhanced Value ETF	72 690 820
SPDR MSCI USA Value UCITS ETF	75 455 100
Ossiam Shiller Barclays CAPE US Sector Value TR	83 488 960
Alpha Architect U.S. Quantitative Value ETF	99 144 050
Vanguard U.S. Value Factor ETF	108 354 500
Fidelity Value Factor ETF	181 715 000
Vanguard Russell 2000 Value ETF	306 619 000
UBS (Irl) ETF Plc - MSCI USA Value UCITS ETF	422 882 700
iShares Russell Top 200 Value ETF	528 059 700
Invesco S&P 500 Pure Value ETF	565 584 300
iShares Edge MSCI USA Value Factor UCITS ETF	1 012 751 000
Vanguard S&P 500 Value ETF	1 158 262 000
Vanguard Russell 1000 Value ETF	2 420 383 000
SPDR Portfolio S&P 500 Value ETF	4 765 593 000
iShares Edge MSCI USA Value Factor ETF	5 511 760 000
iShares Core S&P US Value ETF	5 960 376 000

iShares Russell 2000 Value ETF	7 259 376 000
iShares S&P 500 Value ETF	**15 212 646 078**
iShares Russell 1000 Value ETF	**33 513 723 511**
Vanguard Value ETF	**46 900 000 000**

Value Factor – Europe (Eur)

NAME	ETF AUM
iShares Edge MSCI Europe Value Factor UCITS ETF	2 176 322
SPDR MSCI Europe Value UCITS ETF	2 885 110
Xtrackers MSCI Europe Value Factor UCITS ETF (DR) Capitalization 1C	8 132 636
Deka STOXX Europe Strong Value 20 UCITS ETF	16 587 850
Invesco MSCI Europe Value UCITS ETF	58 023 180
UBS ETF - MSCI EMU Value UCITS ETF (EUR) A-dis	65 921 920
Lyxor MSCI EMU Value (DR) UCITS ETF	131 729 700
iShares Edge MSCI Europe Value Factor UCITS ETF	**938 526 543**

Size Factor - The United States (Usd)

NAME	ETF AUM
BMO S&P US Small Cap Index ETF Trust Units -Hedged-	1 164 910
BMO S&P US Small Cap Index ETF Trust Units	1 196 487
iPath Long Extended Russell 2000 TR Index ETN	1 199 800
First Trust Active Factor Small Cap ETF	1 644 733
Invesco S&P SmallCap 600 UCITS ETF	2 518 590
iShares S&P US Small-Cap Index ETF (CAD-Hedged) Trust Units	2 562 391
iShares S&P US Small-Cap Index ETF Trust Units	3 189 026
Direxion Russell Small Over Large Cap ETF	3 299 069
Invesco PureBeta MSCI USA Small Cap ETF	3 666 475
Direxion Daily Small Cap Bull 2X Shares ETF	3 782 765
PortfolioPlus S&P Small Cap ETF	5 487 400
iShares Factors US Small Blend Style ETF	5 870 320
First Trust Small Cap US Equity Select ETF	7 011 555
BMO S&P US Small Cap Index ETF Trust Units	8 696 318
ProShares UltraShort SmallCap600	8 820 746
Overlay Shares Small Cap Equity ETF	10 772 750
Syntax Stratified SmallCap ETF	12 208 000
ProShares Ultra SmallCap600	14 546 780
Franklin LibertyQ U.S. Small Cap Equity ETF	14 556 000
ProShares Short SmallCap600	16 421 050
Innovator Russell 2000 Power Buffer ETF - April	18 654 080
6 Meridian Small Cap Equity ETF	19 682 310

Invesco S&P Smallcap 600 Equal Weight ETF	22 592 000
Pacer US Small Cap Cash Cows 100 ETF	22 760 000
Timothy Plan US Small Cap Core ETF	23 310 500
Invesco RAFI Strategic US Small Company ETF	25 765 020
Innovator Russell 2000 Power Buffer ETF January	28 310 470
Innovator Russell 2000 Power Buffer ETF - October	36 580 780
BNY Mellon US Small Cap Core Equity ETF	37 093 240
Invesco Russell 2000 UCITS ETF	40 025 210
First Trust Small Cap Value AlphaDEX Fund	45 814 960
Opus Small Cap Value ETF	46 448 380
L&G Russell 2000 US Small Cap UCITS ETF	47 890 850
Smartshares US Small Cap ETF	62 532 920
Goldman Sachs Activebeta U.S. Small Cap Equity ETF	103 641 500
IQ Chaikin U.S. Small Cap ETF	105 581 400
ProShares Ultra Russell2000	117 120 200
JPMorgan Diversified Return U.S. Small Cap Equity ETF	128 040 000
ProShares UltraShort Russell2000	134 971 900
iShares S&P/TSX SmallCap Index ETF	142 967 900
iShares S&P Small-Cap ETF CDI	164 337 000
iShares Morningstar Small-Cap ETF	178 420 100
ProShares UltraPro Short Russell2000	184 376 900
Invesco S&P SmallCap 600 Revenue ETF	201 519 800
ProShares UltraPro Russell2000	206 565 000
iShares US Small Cap Index ETF (CAD-Hedged)	232 875 300
WisdomTree U.S. SmallCap Fund	388 559 800
First Trust Small Cap Core AlphaDEX Fund	389 017 100
iShares MSCI USA Small Cap UCITS ETF	446 731 400
ProShares Short Russell2000	506 746 200
Direxion Daily Small Cap Bull and Bear 3X Shares	642 049 000
iShares S&P SmallCap 600 UCITS ETF USD	710 279 400
Xtrackers Russell 2000 UCITS ETF	806 729 500
Vanguard S&P Small-Cap 600 ETF	901 077 500
SPDR S&P 600 Small Cap ETF	982 607 700
Direxion Daily Small Cap Bull 3x Shares	1 197 840 000
Vanguard Russell 2000 ETF	1 802 551 000
SPDR Portfolio S&P 600 Small Cap ETF	2 116 813 000
Schwab Fundamental US Small Co. Index ETF	2 705 816 000
Schwab U.S. Small-Cap ETF	9 077 783 000
Vanguard Small-Cap ETF	**26 200 000 000**
iShares Russell 2000 ETF	**36 109 325 203**
iShares Core S&P Small-Cap ETF	**39 625 824 228**

Size Factor – Europe (Eur)

NAME	ETF AUM
SPDR EURO STOXX Small Cap ETF	11 105 770
SPDR MSCI Europe Small Cap Value Weighted UCITS ETF	20 357 610
WisdomTree Europe Hedged SmallCap Equity Fund	41 108 940
UBS ETF - MSCI EMU Small Cap UCITS ETF (EUR) A-dis	84 625 870
iShares MSCI Europe Small-Cap ETF	115 858 800
iShares EURO STOXX Small UCITS ETF	385 988 200
Xtrackers MSCI Europe Small Cap UCITS ETF capitalization 1C	574 156 600
iShares MSCI EMU Small Cap UCITS ETF	**639 522 316**

Momentum Factor – The United States (Usd)

NAME	ETF AUM
iShares Edge MSCI USA Momentum Factor Index ETF Trust Units	1 635 448
Principal Sustainable Momentum Index ETF	4 382 609
Invesco S&P 500 Momentum ETF	56 284 840
Alpha Architect U.S. Quantitative Momentum ETF	64 602 000
SPDR S&P 1500 Momentum Tilt ETF	69 947 380
Invesco DWA Consumer Staples Momentum ETF	106 225 400
JPMorgan U.S. Momentum Factor ETF	**112 650 000**
Invesco DWA Momentum ETF	**1 724 600 000**
iShares Edge MSCI USA Momentum Factor ETF	**9 587 664 437**

Momentum Factor – Europe (Eur)

NAME	ETF AUM
iShares Edge MSCI Europe Momentum Factor UCITS ETF	**238 026 717**

ESG Factor – The United States (Usd)

NAME	ETF AUM
Pacer Military Times Best Employers ETF	1 398 950
Barclays Return on Disability ETN	1 424 392
Barclays Women in Leadership ETN	3 636 362
Global X Founder-Run Companies ETF	4 528 845
Impact Shares NAACP Minority Empowerment ETF	5 761 784
Impact Shares YWCA Women's Empowerment ETF	7 371 860
Point Bridge GOP Stock Tracker ETF	8 316 000
BMO MSCI USA ESG Leaders Index ETF	8 943 513

iShares ESG Aware MSCI USA Index ETF	19 482 530
US Vegan Climate ETF	20 459 020
SP Funds S&P 500 Sharia Industry Exclusions ETF	25 414 710
Wahed FTSE USA Shariah ETF	36 977 360
American Customer Satisfaction ETF	52 179 750
IQ Candriam ESG US Equity ETF	55 856 830
iShares MSCI USA Islamic UCITS ETF	68 103 680
FlexShares STOXX US ESG Impact Index Fund	76 203 800
Etho Climate Leadership U.S. ETF	79 131 000
iShares Jantzi Social Index Fund	83 567 530
Inspire 100 ETF	97 662 500
SPDR SSGA Gender Diversity Index ETF	120 015 000
Wealthsimple North America Socially Responsible Index ETF	194 840 800
Xtrackers S&P 500 ESG ETF	201 962 100
Xtrackers MSCI USA ESG UCITS ETF Accum Shs -1C- USD	226 384 000
Global X Conscious Companies ETF	248 543 700
Global X S&P 500 Catholic Values Custom ETF	339 787 700
UBS ETF - MSCI USA Socially Responsible UCITS ETF Class A-dis	1 210 622 000
iShares MSCI USA ESG Select ETF	1 443 633 000
Vanguard ESG U.S. Stock ETF	1 539 175 000
iShares MSCI KLD 400 Social ETF	1 921 729 000
iShares ESG MSCI USA Leaders ETF	**2 255 954 574**
Xtrackers MSCI USA ESG Leaders Equity ETF	**2 251 000 000**
iShares ESG Aware MSCI USA ETF	**6 898 759 240**

ESG Factor – Europe (Eur)

NAME	ETF AUM
iShares Dow Jones Eurozone Sustainability Screened UCITS ETF (DE)	136 636 500
UBS ETF - MSCI EMU Socially Responsible UCITS ETF Class A-dis	823 246 800
iShares MSCI Europe SRI UCITS ETF	**1 624 040 846**

Quality Factor – The United States (Usd)

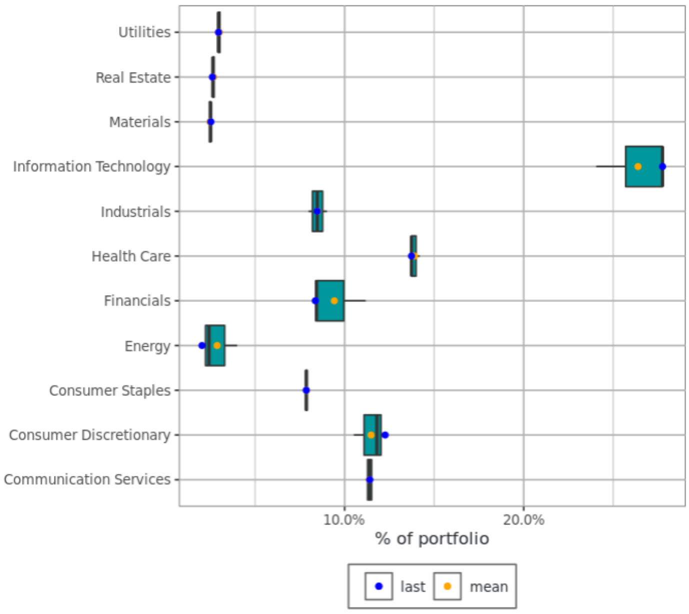
NAME	ETF AUM
Vanguard U.S. Quality Factor	45 060 000
Fidelity Quality Factor ETF	143 670 000
JPMorgan U.S. Quality Factor ETF	**329 830 000**
Invesco S&P500 Quality ETF	**1 938 000 000**
iShares Edge MSCI USA Quality Factor ETF	**17 850 487 767**

Quality Factor – Europe (Eur)

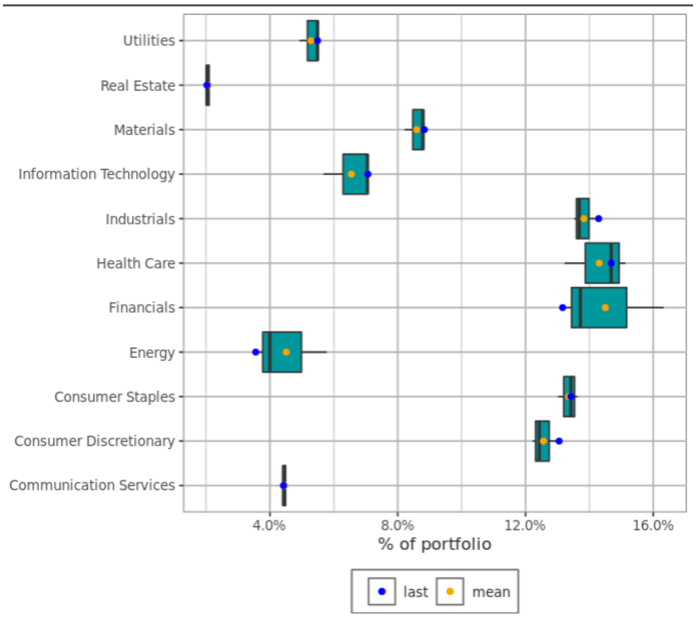
NAME	ETF AUM
iShares Edge MSCI Europe Quality Factor UCITS ETF	133 679 383

Appendix 2. Sector weights for the S&P 500 index and the Stoxx 600 index during the full sample period.

S&P 500:



Stoxx 600:



Appendix 3. Regression Analysis output

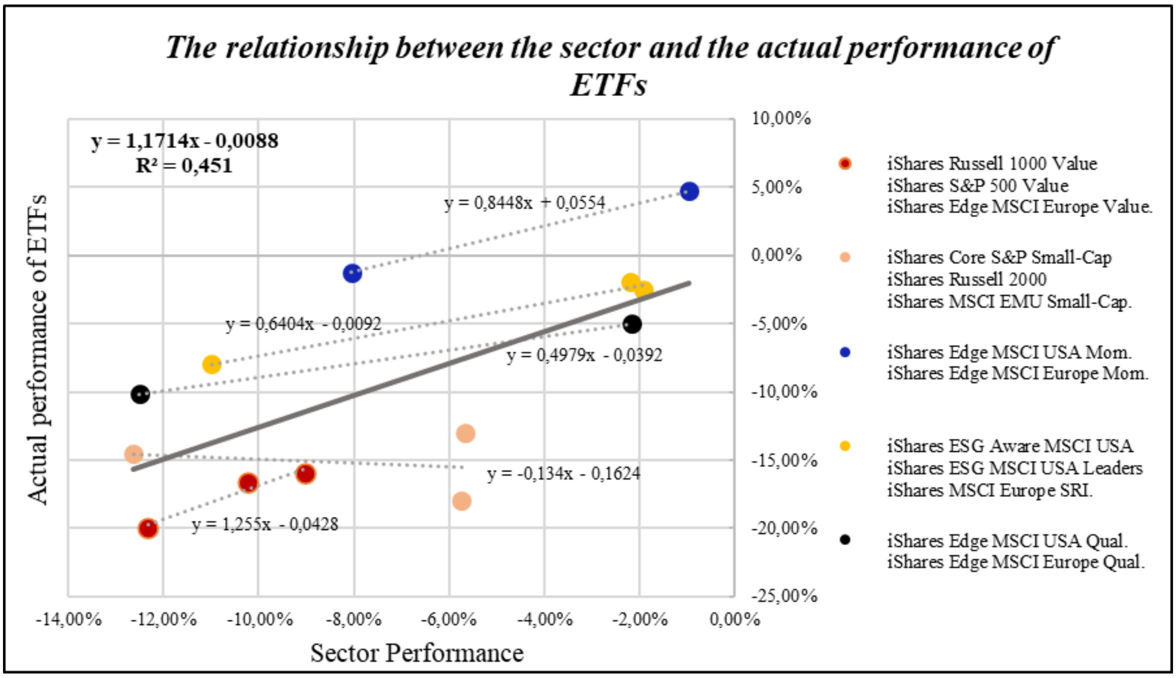
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,671578
R Square	0,451017
Adjusted R Square	0,401110
Standard Error	0,059486
Observations	13,000000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1,000000	0,031978	0,031978	9,037065	0,011947
Residual	11,000000	0,038924	0,003539		
Total	12,000000	0,070902			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-0,008839	0,032756	-0,269827	0,792288	-0,080935	0,063258	-0,080935	0,063258
X Variable 1	1,171385	0,389660	3,006171	**0,011947**	0,313749	2,029022	0,313749	2,029022



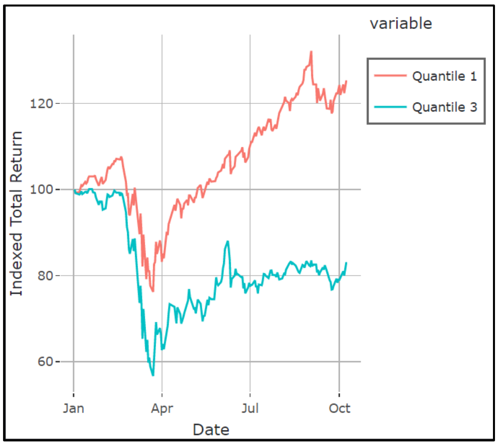
Appendix 4. Sector bets compared to benchmark indices, including the weights of benchmark indices as of 31.12.2019.

ETF	Com.	Con D.	Con S.	Ener.	Finan.	Hcar.	Indu.	Inf Te.	Mate.	Re E.	Util.
iShares Russell 1000 Value	-2,3 %	-4,1 %	1,9 %	4,0 %	10,8 %	-1,1 %	0,7 %	-17,1 %	1,7 %	2,0 %	3,3 %
iShares S&P 500 Value	-2,8 %	-4,5 %	2,5 %	3,7 %	8,4 %	4,2 %	0,8 %	-15,7 %	0,1 %	0,0 %	3,0 %
iShares Edge MSCI Europe Value.	-0,2 %	-0,6 %	0,6 %	-0,1 %	0,0 %	0,0 %	-0,1 %	-0,1 %	0,0 %	0,1 %	-0,1 %
iShares Core S&P Small-Cap	-8,3 %	3,8 %	-2,6 %	0,1 %	4,0 %	-1,8 %	8,7 %	-9,5 %	2,4 %	4,2 %	-1,1 %
iShares Russell 2000	-8,1 %	0,9 %	-3,9 %	-1,0 %	4,6 %	4,1 %	6,9 %	-9,9 %	1,2 %	4,5 %	0,4 %
iShares MSCI EMU Small-Cap.	2,6 %	-1,6 %	-10,7 %	-3,6 %	-4,7 %	-5,3 %	7,3 %	5,4 %	-0,2 %	10,0 %	0,7 %
iShares Edge MSCI USA Mom.	-3,0 %	-3,9 %	1,5 %	-4,2 %	-6,3 %	-3,4 %	-2,2 %	2,9 %	1,3 %	8,3 %	8,7 %
iShares Edge MSCI Europe Mom.	-2,9 %	0,8 %	-2,0 %	-6,3 %	-6,2 %	7,1 %	3,3 %	3,8 %	-3,4 %	0,5 %	4,8 %
iShares ESG Aware MSCI USA	-0,7 %	-1,0 %	0,1 %	-0,1 %	-0,8 %	-0,2 %	0,9 %	0,8 %	0,3 %	0,0 %	0,4 %
iShares ESG MSCI USA Leaders	-0,1 %	0,5 %	0,2 %	-0,3 %	-0,9 %	-0,1 %	0,2 %	0,1 %	0,1 %	0,0 %	0,1 %
iShares MSCI Europe SRI.	0,1 %	0,1 %	1,6 %	-5,9 %	1,3 %	-0,4 %	1,1 %	2,9 %	0,7 %	0,4 %	-2,3 %
iShares Edge MSCI USA Qual.	0,0 %	0,3 %	0,1 %	-0,1 %	-0,2 %	-0,2 %	0,2 %	-0,2 %	0,0 %	0,0 %	-0,1 %
iShares Edge MSCI Europe Qual.	0,1 %	0,0 %	-0,4 %	0,1 %	0,0 %	-0,3 %	0,1 %	-0,1 %	0,1 %	0,1 %	0,0 %
MSCI USA Index	10,4 %	9,9 %	7,0 %	4,2 %	13,0 %	14,1 %	9,0 %	23,4 %	2,7 %	3,2 %	3,3 %
MSCI Europe Index	4,4 %	10,1 %	13,9 %	6,7 %	18,0 %	13,8 %	13,7 %	6,2 %	7,3 %	1,4 %	4,4 %

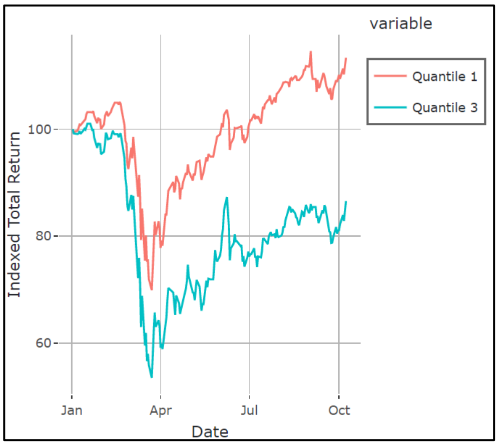
Appendix 5. Performance of pure factor portfolios

U.S. Value (Market cap-weighted)

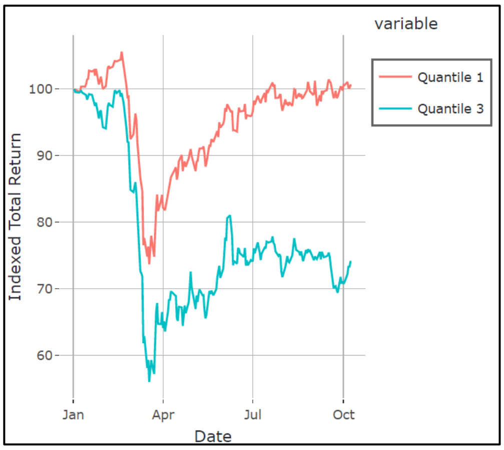
Quantile 1 (High P/B, P/E), Quantile 3 (Low P/B, P/E)



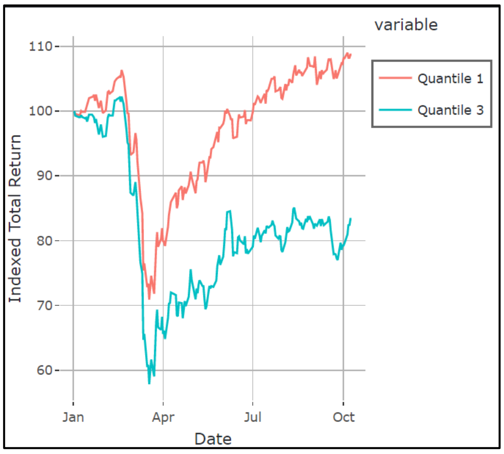
U.S. Value (Equally-weighted)



Europe Value (Market cap-weighted)

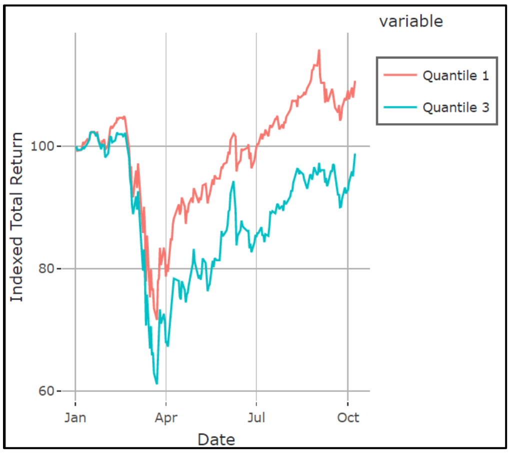


Europe Value (Equally-weighted)

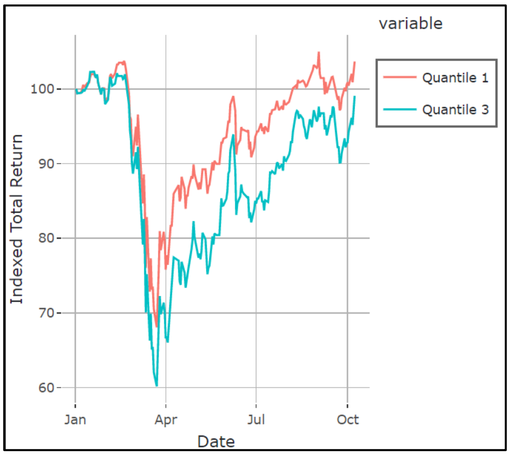


U.S. Size (Market cap-weighted)

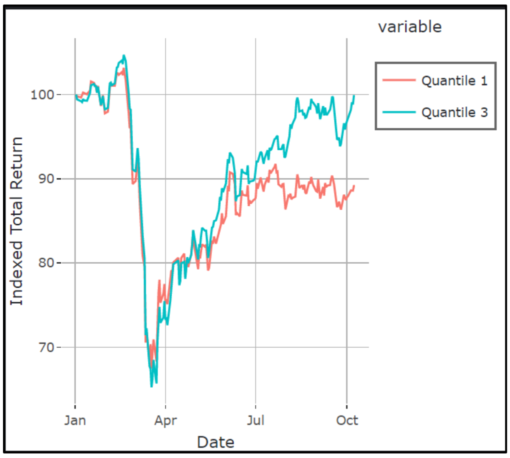
Quantile 1 (Large-cap), Quantile 3 (Small-cap)



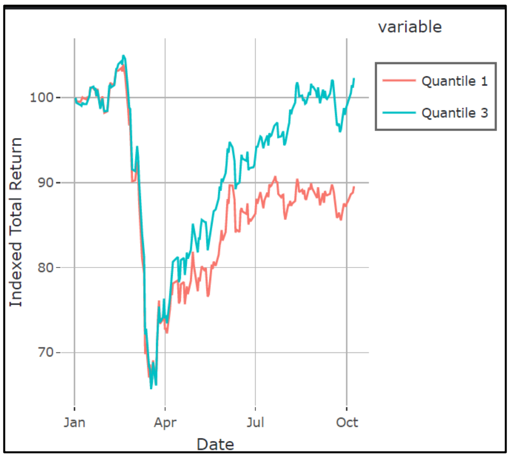
U.S. Size (Equally-weighted)



Europe Size (Market cap-weighted)

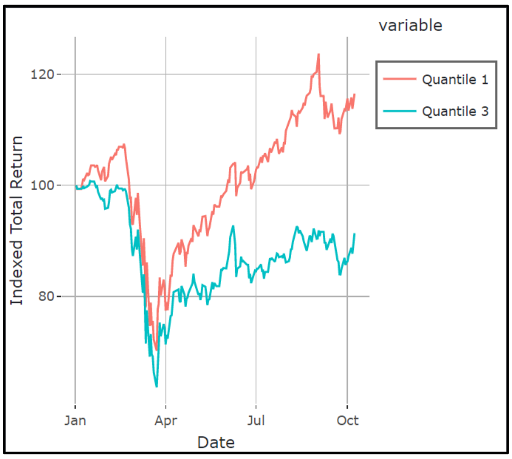


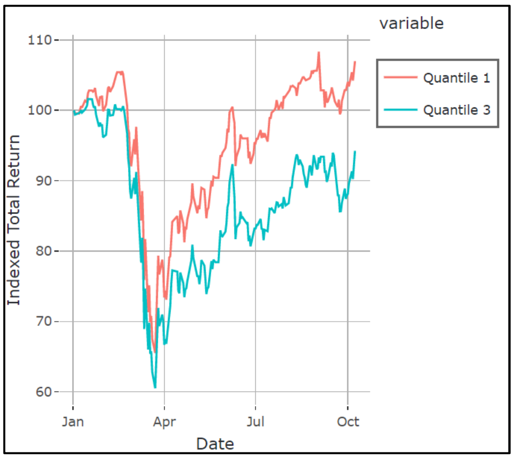
Europe Size (Equally-weighted)



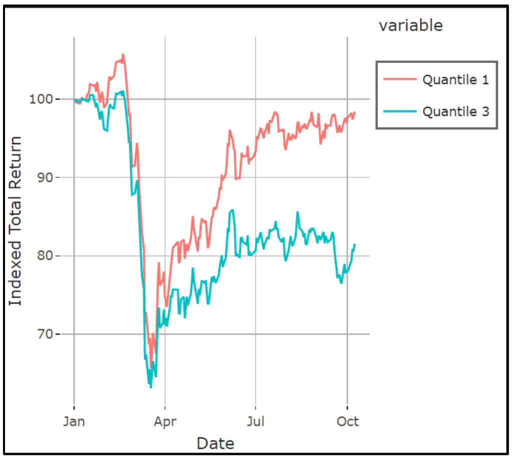
U.S. Momentum (Market cap-weighted) *U.S. Momentum (Equally-weighted)*

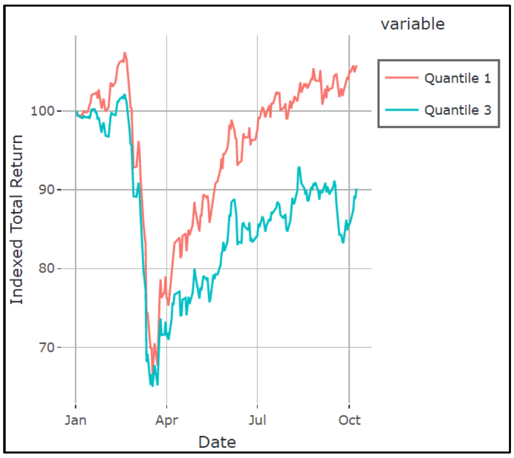
Quantile 1 (High Momentum) Quantile 3 (Low Momentum)





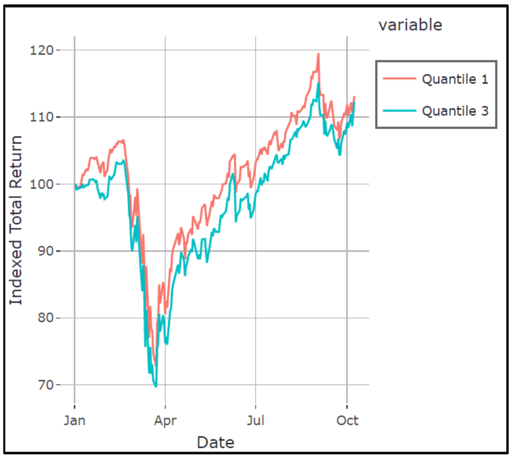
Europe Momentum (Market cap-weighted) *Europe Momentum (Equally-weighted)*

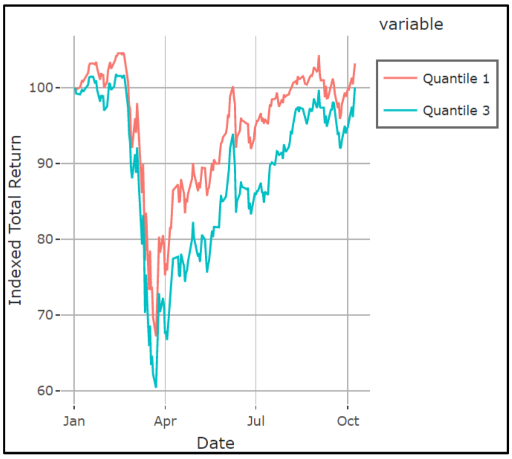




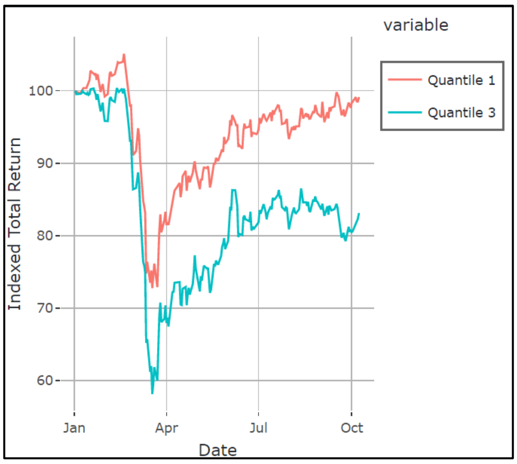
U.S. Quality (Market cap-weighted) *U.S. Quality (Equally-weighted)*

Quantile 1 (High ROE-% & EBIT-%) Quantile 3 (Low ROE-% & EBIT-%)

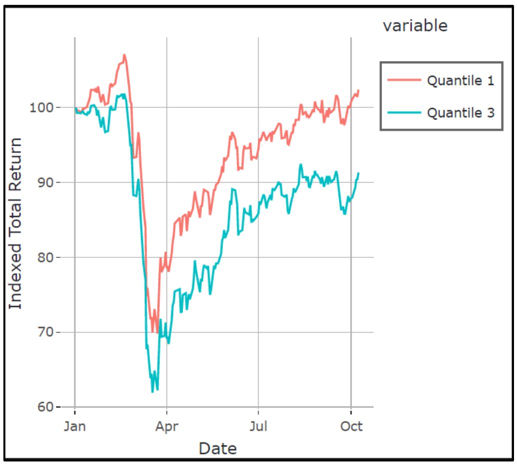




Europe Quality (Market cap-weighted)

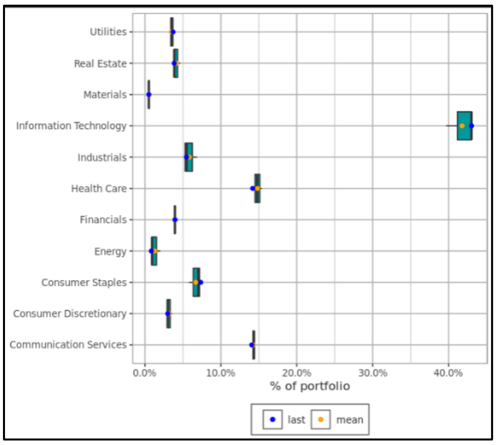


Europe Quality (Equally-weighted)



Appendix 6. Sector mix of quality pure factor portfolios

U.S. Quality (Market cap-weighted)



Europe Quality (Market cap-weighted)