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Performance of Value and Growth companies with different ESG rankings:

Evidence from the US stock market

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ABSTRACT

The purpose of this paper is to focus on sustainable investments and to observe if the performance can be improved by combining the aspect of value and growth investments. The sample consists of groups of companies which are representing value or growth with either high or low ESG risk level. Different portfolios are constructed based on these groups between a time-period of 2 November 2016 and 26 February 2021, and performances of the portfolios are estimated by using the CAPM, Fama-French three-factor model, Carhart four-factor model, and different performance ratios. The risk-adjusted performance order of the constructed portfolios is estimated with the alpha-values of the factor-models and supported with the measures of the performance ratios. The study finds that the combined effect of both value/growth and ESG risk can be observed contributing the outperformance of the growth portfolio when compared to the performances of the other constructed portfolios, especially when increasing the EGS risk of this portfolio. This result is significant and supported by all the models computed in this research. The found evidence is not in line with the previous research which makes the studied combination not being unambiguous.

Keywords: ESG Risk, Value Stocks, Growth Stocks, Portfolio Performance, CAPM, Factor Models

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1. INTRODUCTION

In organizational management, responsible aspects have become one of the most central competitive advantages. *Inter alia*, Eweje and Perry (2011) point out that shareholders, other stakeholders, and researchers are getting more aware of the importance of the responsible issues which has further affected on the business practices and performance expectations of the organizations. The awareness has led to investments in responsible performance increasingly which has been seen as a contributor for the future business performance and improvement.

The organizational responsibility can be divided into three dimensions. As Ferrell and Hartline (2019) list, environmental attention covers issues related to climate, pollution, waste, and natural resources. The social attention covers human capital treatment, product subjection, stakeholder opposition, and different social opportunities in connection to the company. Whereas the governance attention covers the ethics and transparency in the corporate governance and the behavior related to corruption and anti-competitive behavior. With this framework, it is possible to compartmentalize companies into responsible and irresponsible ones. Thus, different data-focused organizations rank companies based on different levels of ESG risk. Sustainalytics (2021a) suggest that the purpose of such rankings is to generate data and information about sustainability in policies, practices and capital design of hundreds of companies and their financial instruments, and to provide this information to different shareholders. The total ESG risk score of a company is calculated by reducing the management risk from the company's risk exposure (Sustainalytics, 2021a).

The research of this paper addresses performances of fictive constructed portfolios with different weights of selected US growth and value stocks covering both high and low ESG risk between a time-period of 2 November 2016 and 26 February 2021. Since the performance of sustainable investments vary across different studies, the goal of the research is to focus on sustainable investment and to observe if the performance can be improved by combining the aspect of value and growth investments. The previous research has confirmed repeatedly that value stocks tend to outperform growth stocks over time. This claim has been evidenced *inter alia* by Fama and French (1998), Lakonishok, Shleifer and Vishny (1994), and Davis (1994). Whereas studies carried out about the performance of investments that can be considered sustainable have proven that over time they tend to outperform the investments that can be seen being irresponsible to some extent. This has been evidenced *inter alia* by Serafeim (2014) and Friede, Busch and Bassen (2015). Thus, with reference to the previous studies, it could be assumed that value investments with low ESG risk would be the ones that perform the best in the market.

With regards to the above, the research aims to answer the following question:

By combining the previously proved outperforming aspects of growth/value investments, and investments with certain ESG level, can value portfolio representing low ESG risk be seen performing the best among all the constructed portfolios?

Different performance measures are used to study the research question. The used models cover the Capital Asset Pricing Model (with Jensen's performance index), Sharpe ratio, Treynor's performance index, and Information ratio. The Capital Asset Pricing Model will be used as the central model in the study, which will be computed with two different additional factor models; Fama-French three-factor model and Carhart four-factor model. The selected models are used as most of the models are widely assessed by the corresponding literature with regarding to valuating portfolios.

Despite the outcome of the previous referenced studies with respect to performance of value/growth and ESG-related investments, these separate findings are observed to be proven wrong when combining these two aspects in one portfolio. It is found that according to all the used models, the best performing portfolio is the growth portfolio with majority of high ESG risk where the worst performing portfolio is the value portfolio with majority of low ESG risk. The study finds that value/growth attribute of the investment is stronger than the influence of the market on the ESG aspect when using the portfolio return changes as a proxy. According to the study executed by DiCiurcio *et al.* (2021), in the recent years the underperformance of value stocks has been obtained due to the low inflation rates, high volatility, and certain type investing boom in the newer high-tech companies. On the other hand, despite the high volatility in 2020 (mainly caused by the Covid-19 pandemic) Fidelity's (2020) study showed that globally, the top ESG rated investments still outperformed the low ESG rated investments and stayed stable.

In its entirety, the paper covers four parts. The first part includes a literature review where the background and previous studies behind the research are introduced and assessed. First, the literature review introduces the link between ESG and organizations. Then the performance and previous studies in the area of growth and value investments, and investments that are considered responsible are discussed. The rest of the chapter focuses on the evaluation methods used in this paper. The second part, Data and Methodology, introduces the data selection and collection process, covers theoretical aspect of the ESG rating and benchmarking, and presents the portfolio construction and used methodology. The paper proceeds to the diagnostic testing for the data, and in the last part, first, interesting features of the constructed portfolios in the shape of descriptive statistics are interpreted, and then the results of the executed models are reviewed and analyzed in more detail.

2. LITERATURE REVIEW

This chapter outlines and describes the background to the topic of the thesis, emphasizes the most common research outcomes, and describes the evaluation methods used in this paper. In more detail, first the ESG framework is described, and the components of this framework are introduced, then the general performances of both value/growth and ESG aspects are observed. In the end the evaluation methods; the CAPM, factor models, Jensen's performance index, Sharpe ratio, Treynor's performance index and Information ratio are introduced, and their mathematical computations are presented.

2.1 ESG framework

Sustainable and responsible aspects are part of the central competitive advantage in today's organization management. Eweje and Perry (2011) point out that different shareholders, stakeholders, and researchers have become more aware of the organizational responses to green and social issues, which has also started certain kind of boom in research. The awareness has lead companies considering increasingly responsible impacts in their business practices. They also emphasize that when it comes to the responsible modifications, the performance expectations have seen varying from marginal improvements in resource controlling to fundamental modification in the business practices of the whole organization. However, as one of the most important features of the increasing awareness of sustainability in business according to Eweje and Perry (2011) is that the investments in responsible performance will support and drive the future business performance and improvement.

Sustainability of system development in organizations can be divided into three dimensions. Ferrell and Hartline (2019) list that the environmental attention covers issues related to climate, pollution, waste, and natural resources. The social attention covers human capital treatment, product subjection, stakeholder opposition, and different social opportunities in connection to the company. Whereas the governance attention covers the ethics and transparency in the corporate governance and the behavior related to corruption and anti-competitive issues. This framework usually refers to investment targets that can be considered socially responsible and ethical, and in general can be used as a tool to avoid companies with unethical and environmentally unfriendly strategies (Ferrell & Hartline, 2019).

2.2 Performance of growth and value companies

Growth company is defined widely as a company that grows faster than an average company over long term which earns adequate return on its investors' money. Whereas a growth stock is a publicly

traded entity of a growth company (Martin, 2011). According to a study by Lakonishok, Shleifer and Vishny (1994), companies with high growth usually have low earnings-to-price, cash-flow-to-price and book-to-market ratios. But when it comes to value companies, they are not widely described, but according to Morningstar (2021b), the stocks of value companies are less expensive and growing more slowly than the other stocks. However, classified by investment managers, these stocks tend to have high book-to-market, earnings-to-price and cash-flow-to-price ratios (Fama & French, 1998).

When investing in value entities, the behavior of this entity can be seen reminding somewhat fixed-income securities. The future growth is not potentially high, but the reasonable profitability can be formed by dividends and capitalizing on the difference of the stock price and inherent value (Martin, 2011). There are many showings that in time, value stocks would tend to have higher returns than growth stocks. For instance, according to Fama and French (1998), value stocks outperform growth stocks when it comes to their study between 1975 and 1995 in twelve of thirteen major markets. It is also proved that especially in the US markets, the value premium tends to be high in average (Lakonishok, Shleifer & Vishny, 1994). Another study made by Davis (1994) supports this finding. On the other hand, a study executed by Beneda (2002), studied returns of stocks with high price-to-earnings ratios versus returns of so-called value stocks, and suggested that when investigating 18 year's performance (relatively long term), the growth stocks outperformed the value stocks in over 14 years of the period. After five years however, the value stocks started to outperform the growth stocks, which supports again the other previous studies.

Nevertheless, some explanations for the outperformance of value stocks have been expressed. One of the reasons is the statistical fluke. According to Veale (2014), it is visible that it can be dependent on the sample and time-period whether growth or value stocks outperform each other. In this case it can be interpreted that the luck has hit value stocks more than growth stocks when it comes to most of the previous studies and their outcome. The second explanation of value stocks' outperformance can be related to the survivorship bias (Veale, 2014). Most of the previous studies cover a long time-period, which includes only a sample of survived companies. In reality, when the losses of the bankrupted companies would be considered, the outcome would potentially be very different. Vaele (2014) also brings out that another reason could be lack of risk adjustment. The reason for many value stocks' outperformance is the higher level of risk. In the previous studies the value stocks must have therefore had similar returns to the growth stocks in the risk adjusted base. In general, value stocks tend to have lower beta, and lower volatility than growth stocks, which means that in that case the risk cannot be higher for value stocks (Veale, 2014).

2.3 Performance of ESG investments

Different studies are executed increasingly about the performance of different ESG-related investments, especially about certain funds, bonds, or stocks that represent sustainable solutions. Aside of studies of these types of investments, the attention is also focused on conventional companies that increasingly can be considered having sustainable values. Since nowadays investors are more aware of the ESG risks of different industries, it can be seen affecting on their willingness to invest in certain companies. Recent example of how ESG awareness of the investors can have effect on the investment decision is the China retaliation over dropping cotton produced by forced labor, reported by MarketWatch (2021). This news has influenced many European-listed clothing companies by downing the stock price sharply inside the next few days from the news. Serafeim states that "The more customers, employees, investors and local communities expect from companies to perform their functions in responsible ways the more responsible companies will be rewarded, and irresponsible companies will be punished." (2014, p. 15). Today, the ESG factors have adapted into the so-called conventional investing strategies as well. For instance, Van Duuren, Plantinga and Scholtens (2016) emphasize that ESG information has been used to manage risk and to red flag the conventional fund management. However, indicating that it is different how the US asset managers view ESG compared to the European asset managers. The managers in the USA are more skeptical when it comes to the benefits of the ESG views (Van Duuren, Plantinga & Scholtens, 2016).

George Serafeim (2014) compared two sets of companies which were different with their corporate policy sustainability, but otherwise similar by their size, industry status, growth expectations and financial performance. The aim of the research was to study the correlation of sustainability and performance between years 1993 and 2010. Out of the studied 180 US firms, 90 were considered highly sustainable, and the rest 90 were considered having low sustainability. The outcome of the study showed that the sustainable companies outperformed significantly compared to the conventional ones where the outperformance was recorder to be around 4.8% yearly. In one of the widest studies about ESG performance, Friede, Busch and Bassen (2015) combined around 2200 empirical studies which handled the relation between ESG criteria and corporate financial performance. The study found a comprehensive nonnegative relation between ESG and corporate financial performance, and this impact over time appeared to be stable.

2.4 Evaluation methods

For this study, the following performance measurement models are selected: the Capital Asset Pricing Model, Sharpe ratio, Treynor's performance index, Jensen's performance index and Information

ratio. Capital Asset Pricing Model is used as the central model in the study, which is computed with different factor models; Fama-French three-factor model and Carhart four-factor model.

2.4.1 The Capital Asset Pricing Model

As Fama and French (2004) express, Capital Asset Pricing Model of Sharpe (1964) and Linter (1965) can be said to be the foundation for the asset pricing theory. This model has been used to estimate the cost of capital and to determine the performance of different portfolios over time. The power of the model comes from wide predictions of risk measurement and the relation between the risk and expected return. One of the downsides of the model is that it usually limits the sample portfolios to US common stocks (Fama and French, 2004). One of the benefits of this model is that it considers the systematic risk (β_p). This feature makes this model reflecting comprehensively to the stock market. CAPM can be calculated as:

$$r_p - r_f = \alpha_p + \beta_p RMRF + \varepsilon_p \tag{1}$$

Where r_p is the return of the portfolio, r_f is the risk-free rate, β_p is the coefficient of the excess market return of the portfolio, $RMRF$ is the excess market return and ε_p is the error term of the portfolio.

2.4.2 Fama-French three-factor model

The so-called Three-factor model by Fama and French (1993) was developed in 1992 for asset pricing, using the CAPM as its frames. This model was created due to the limitations of the original CAPM. One of the biggest limitations of the CAPM was that it ignored the effect that high returns would follow high earnings to price ratios. Beta's power should be therefore all that matters, whereas according to CAPM, it was not (Basu, 1983). Another study, computed by Banz (1981) suggested that companies with low market capitalization tend to have higher mean returns than ones with higher capitalization. This is also contradictory with the CAPM. So, the Fama-French three-factor model added the size premium and value premium to the market risk factor, which makes the portfolio to adapt better with the portfolio return variation (Fama & French, 1993). The model can be calculated as follows:

$$r_p - r_f = \alpha_i + \beta_{1p} RMRF + \beta_{2p} SMB + \beta_{3p} HML + \varepsilon_p \tag{2}$$

Where r_p is the return of the portfolio, r_f is the risk-free rate, β_{1p} is the coefficient of *RMRF* of the portfolio, β_{2p} is the coefficient of *SMB* of the portfolio, β_{3p} is the coefficient of *HML* of the portfolio, $RMRF$ is the excess market return, SMB is the size premium, HML is the value premium and ε_p is the error term of the portfolio.

2.4.3 Carhart four-factor model

Following Carhart (1997), the four-factor model was constructed based on the Fama-French three-factor model where an additional price-momentum factor was added as a systematic risk-factor. Here the premia and the coefficients on the factor mimicking portfolios demonstrate the fraction of mean return available to four elementary approaches (more about the momentum-factor in the chapter 3.3 Benchmarking and factor mimicking portfolios). The four-factor model can be expressed as:

$$r_p - r_f = \alpha_i + \beta_{1p}RMRF + \beta_{2p}SMB + \beta_{3p}HML + \beta_{4p}MOM + \varepsilon_p \quad (3)$$

Where r_p is the return of the portfolio, r_f is the risk-free rate, β_{1p} is the coefficient of $RMRF$ of the portfolio, β_{2p} is the coefficient of SMB of the portfolio, β_{3p} is the coefficient of HML of the portfolio, β_{4p} is the coefficient of MOM, $RMRF$ is the excess market return, SMB is the size premium, HML is the value premium, MOM is the momentum factor and ε_p is the error term of the portfolio.

2.4.4 Sharpe ratio

Sharpe ratio, one of the most used performance measures, is used to measure the relationship between the average excess return over time and the standard deviation of the excess returns of the portfolio (see Equation 4). In other words, it is a profitability measure using the volatility of the investment (Sharpe, 1966). However, as Ornelas, Silva Júnior and Fernandes (2012) suggest, this measure is suitable only if the investors believe in risk measuring based on standard deviation and to normal distribution of the returns. According to Morningstar's dictionary (2017), The relationship between profitability and Sharpe ratio can be interpreted as the higher Sharpe ratio, the better the returns are relative to the taken risk (risk-adjusted performance).

$$Sharpe\ ratio = \frac{r_p - r_f}{\sigma_p} \quad (4)$$

Where r_p is the return of the portfolio, r_f is the risk-free rate and σ_p is the standard deviation of the portfolio.

2.4.5 Treynor's performance index

Treynor's performance index or Treynor index is similar performance measure tool as Sharpe ratio, but instead of using standard deviation as a measure of the risk, it uses the beta of the investment (see Equation 5) (Madura, 2015). Treynor index is not dependent on leverage such as Jensen's performance index, which makes it an intrinsic measure (Brugiere, 2010). The relationship between profitability and Treynor's performance index again can be interpreted as the higher the index, the greater the returns related to the risk-free rate (Madura, 2015).

$$Treynor's\ performance\ index = \frac{r_p - r_f}{\beta_p} \quad (5)$$

Where r_p is the return of the portfolio, r_f is the risk-free rate and β_p is the risk parameter (estimated).

2.4.6 Jensen's performance index

Jensen's performance index or Jensen's alpha measures the difference between the actual mean return yielded by the investment, the equilibrium returns and the overall risk level of the investment, while considering the market conditions (Jensen, 1968). This measure can be said being the intercept in time series regression of excess returns against the excess returns time series on the benchmark, which in fact regarding the Capital Asset Pricing Model can be used as a measure of the investment's average performance in excess of the return. In this model, Jensen's alpha is the component of the investment selection ability, where a positive alpha refers to good fund management and a negative to contrary fund management and to performance that does not meet the expectations (Zopounidis, 2002). Jensen's performance index is the alpha from the following equation:

$$(r_p - r_f) = \alpha_p + \beta_p(r_m - r_f) + \varepsilon_p \quad (6)$$

Where r_p is the return of the portfolio, r_f is the risk-free rate, r_m is the return of the market portfolio, α_p is the Jensen's alpha, β_p is the risk parameter (estimated) and ε_p is the error term of the portfolio.

2.4.7 Information ratio

According to Lee (2000), Information ratio (IR) or Alpha-omega ratio can be said being a performance measure which is more or less aggressiveness independent. The aggressiveness behind it can be associated to the alpha of a fund manager that can be higher than others just because they can be more aggressive in making bets. The alpha gets more spread when the aggressiveness increases. This can then lead to higher alpha and tracking error. Information ratio can therefore be used to remove the aggressiveness from the real profitability (Lee, 2000). One of the benefits of this model is that it can be used to measure the performance on its benchmark and adapts it for the volatility. Here again, the higher the ratio is, the more profitable is the investment.

$$Information\ ratio = \frac{\alpha_p}{TE} \quad (7)$$

Where α_p is the alpha (Jensen's alpha) of the CAPM and TE is the tracking error.

3. DATA AND METHODOLOGY

This chapter presents the procedures behind the models used. In more detail, first the data selection and collection process are introduced, then more detailed procedures of the ESG and benchmarking data are explained. In the end the construction of the portfolios and the methods computed are presented.

3.1 Data

Since this study focuses on performances of fictive constructed portfolios with different weights of selected US growth and value stocks covering both high and low ESG risk, the data collection process consists of several parts. The actual data of daily closing stock prices of the target companies are collected by using the Bloomberg terminal between a time-period of 2 November 2016 and 26 February 2021, however using Morningstar's listings and Sustainalytics' ratings to specify the sample for this study.

The growth and value companies are selected from Morningstar's growth and value company listings for mid-cap and large-cap companies in the USA with a common currency, US dollar. As a criterion for the growth companies, Morningstar (2021a) uses a measurement of projected growth. Such companies are growing faster compared to their peers in certain size category, and here a growth company represents high growth rates of book value, cash-flow and earnings, and high price ratios and low dividend. On the other hand, as a criterion for the value companies, Morningstar (2021b) uses less expensive stocks, and slower growth when comparing to other stocks in the certain size-category. In addition, the website considers low valuations, from high dividend yields and low price-ratios, and growth that is slower, from lower growth rates of book value, cash-flow, and earnings.

A relatively short time-period of 2 November 2016 - 26 February 2021 is selected since it cannot be assumed that the target companies have the same features of growth or value companies in a long term, or that the ESG risk remains the same for each company. The specific time-period is also limited since some of the important companies were not established before 2 November 2016 which makes it important to slightly cut the time-period. Also, the data for the factor mimicking portfolios and additional factors to the factor models is limited to 26 February 2021 in the Kenneth R. French data library in the moment when collecting the data.

In order to classify the companies based on their ESG risk, Sustainalytics-website is used. Further, only the growth and value companies that satisfy the certain ESG risk-levels are selected. As the low ESG risk companies, this study considers only companies that are ranked to carry ESG risk level of

under 20. Whereas as the high ESG risk companies, this study considers only companies with ESG risk above 27. 27 is selected to be the minimum rating for the risky companies since there are not enough companies ranked above 30 (which is the minimum level for "high risk" companies according to Sustainalytics). The aforementioned adjustment to the method is necessary in order to construct even portfolios. In the end, calculated by the author, 27% out of all the Morningstar's listed mid-cap and large-cap value companies are considered having a low ESG risk, and 22% having a high ESG risk. Whereas 22% out of all the Morningstar's listed mid-cap and large-cap growth companies are considered having a low ESG risk, and only 12.5% having a high ESG-risk. In order to use the collected data in the following methodologies, the stock prices are converted into daily returns by using the natural logarithm (see Equation 8).

$$r_t = ln\left(\frac{p_t}{p_{t-1}}\right) \tag{8}$$

It can be observed from the daily return characteristic-table below (see Table 1) that over the time-period of 2 November 2016 - 26 February 2021, the growth companies that have a high ESG risk have the highest daily returns in average, whereas the value companies with a high ESG risk have very low average daily returns. Since the standard deviations of all the company groups are relatively low, it can be observed that there is not much variation when it comes to the daily returns. Yet, for all the company groups, the skewness is negative. This implicates that the data is skewed to the left. When it comes to the kurtosis, it can be noticed that it is relatively high for all the groups. However, for the value companies that have a high ESG risk, the kurtosis is very high. High kurtosis usually refers to heavy tails or outliers. But in this case, as the standard deviation is low for all the groups, there is probably only few existing extreme data points. Otherwise, the maximum and minimum daily returns are similar for all the groups except the growth companies with a high ESG risk have the highest maximum return, and the value companies with a high ESG risk have the lowest. The more detailed yearly daily return characteristics are calculated in the tables attached as Appendix 1.

Table 1. Descriptive statistics of the company groups

	No. of Companies	Mean	St. Dev.	Skewness	Kurtosis	Max	Min
Growth Low	24	0.129 %	2.442 %	-0.410	14.567	29.985 %	-31.455 %
Value Low	24	0.024 %	2.109 %	-0.557	18.797	24.584 %	-31.078 %
Growth High	24	0.130 %	2.895 %	-0.157	16.370	41.677 %	-39.529 %
Value High	24	0.003 %	2.473 %	-2.425	75.058	29.041 %	-76.411 %

Table 1 shows the daily return characteristics of the four company groups covering the whole period from 2 November 2016 to 26 February 2021. The table indicates the number of the companies included in the group, mean, standard deviation, skewness, kurtosis, maximum and minimum of the daily returns of each group. Here, Growth Low refers to growth companies with low ESG risk, Value Low refers to value companies with low ESG risk, Growth High refers to growth companies with high ESG risk, and Value High refers to value companies with high ESG risk.

3.2 ESG ranking

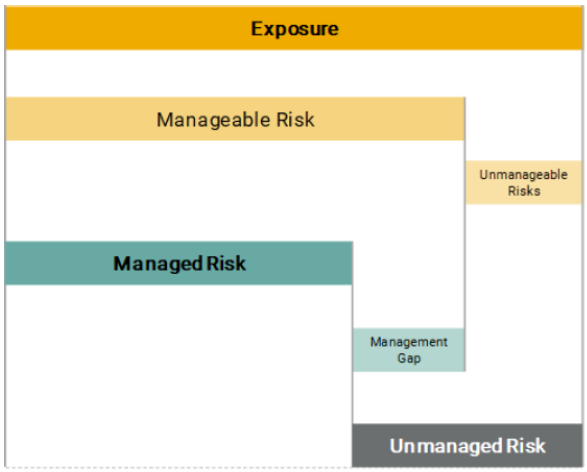
Different data-focused organizations such Bloomberg and Sustainalytics rank companies based on different levels of ESG risk. The purpose of such rankings is to generate data and information about sustainability in policies, practices and capital design of hundreds of companies and their financial instruments (Sustainalytics, 2021a). When it comes to the ESG ranking according to Sustainalytics (2021a), the ratings can be based of different blocks such corporate governance, material ESG issues and idiosyncratic ESG issues. The blocks according to the website can be described as follows. Corporate governance in this case represents a connection between governance and material risks. This fundamental element can be seen contributing around 20% of the overall unmanaged risk rating of each company. On the other hand, material ESG issues cover management initiatives such diversity, engagement, labor relations and development, and it can be seen occurring at the subindustry level, however only if it is relevant to the business model of the company. This block is important when it comes to differentiating between systematic and unpredictable ESG issues which makes it the center of the risk rankings. Whereas the idiosyncratic block represents issues that can be unexpected in the specific subindustry where the company is working, accounting scandal as an example. Idiosyncratic issues can become material for a certain company in cases where the identified event assessment reaches the significant threshold (Sustainalytics, 2021a).

Sustainalytics (2021a) splits the dimensions of the risk ratings into two dimensions; exposure and management, and according to the website, the splitting refers to the exposure of material ESG risks in individual and overall level, and to the management disclosure where the exposure can be considered as a vulnerability to different ESG risks of the company. For companies that work in the same industry, the determination of the exposures can be assessed based on the companies' structured external data, reporting, research of the third-party and event track record. However, using beta-

assessment, the ESG risk ratings can be made firm-specific. The website emphasizes that this means that the measured company's exposure of material ESG issues is compared to the subindustry's exposure. Here the company's exposure score is calculated by multiplying the issue beta of the company by the exposure score of the subindustry. Sustainalytics further splits the used beta indicators into four different areas. These are geographic, financials, product and production, and events. In order to calculate the issue betas, the qualitative overlay (additional factors) and correlation factor (average beta) are added to the beta indicators (Sustainalytics, 2021a).

In ESG rating, the considered risk can be either manageable or only partly manageable. In the case of Sustainalytics (2021a), the manageable risk is determined in subindustry level, and when setting the factors for manageable risk, conformity to employees, cybersecurity, issue complexity and technology innovation are considered. Another important factor in this ESG ranking is the dimension of management which considers the way the company is managed from commitments and actions' point of view. Further, the score for management can be calculated based on different management- and outcome-adjusted indicators. The ranking-website brings out that the management adjusted indicators can be different management policies or regimes. Whereas the outcome-adjusted indicators are used to measure the management in terms of quantitative measures. Here the indicators can be split into management indicators (managing the ESG issues) and event involvement indicators (controversial events associating with society and environment) (Sustainalytics, 2021a).

Sustainalytics (2021a) calculates the ESG risk ratings in three steps (see figure 1). First the exposure is resolved, then the management level and its risks are determined, and lastly, the unmanaged risk is resolved. The ESG risk ratings score in the end is calculated by reducing the managed risk from the company's exposure.



Company Exposure	=	Subindustry Exposure	*	Issue Beta		
	=	8	*	1.5	=	**12**
Manageable Risk	=	Company Exposure	*	MRF		
	=	12	*	90%	=	**10.8**
Managed Risk	=	Manageable Risk	*	Management score (as %)		
	=	10.8	*	75%	=	**8.1**
Unmanaged Risk	=	Company Exposure	-	Managed Risk		
	=	12	-	8.1	=	**3.9**

Figure 1. ESG risk rating scoring from Sustainalytics' point of view (Sustainalytics, 2021a)

In the end, the ESG risk ratings can be distributed into five different categories. These exposure and management categories are comparable regardless the industries and represent an absolute measure of risk. The different scales of risks for different companies are negligible: 1-10, low: 10-20, medium: 20-30, high: 30-40 and severe: +40. The lower the company's ESG risk rating is, the lower its overall risk is (Sustainalytics 2021c).

Negligible	Low	Medium	High	Severe

Figure 2. ESG risk rating categories from Sustainalytics' point of view (Sustainalytics, 2021b)

3.3 Benchmarking and factor mimicking portfolios

Since the portfolios in this study are constructed only from the US stocks, the factor portfolios are constructed based on the Kenneth R. French data library. This data library consists of Fama-French factors, where the factor proxies are RMRF (excess return of the market), SMB (small Minus Big), and HML (High Minus Low) (French, 2021). MOM (Momentum Factor) will be introduced as an additional factor for the four-factor model of Carhart (1997). Here RMRF is the average premium per unit of market beta where the market index is constructed based on data from CRSP (Center for Research in Security Prices) on companies that are based in the US, listed on the NYSE, NASDAQ and AMEX, and other requirements such carrying 10 or 11 as the CRSP share code (Fama & French, 1993). In this study, the market described above is used as the market benchmark.

Fama and French (1993) express that the SMB-factor proxy is described to be every month's mean return of the difference between the three small portfolios and the mean return on the three large portfolios where the purpose is to mimic the risk factor in returns when linking to size. These small- and large-stock portfolios have been seen having approximately the same weighted-average book-to-market equity. SMB includes stocks from NYSE, NASDAQ and AMEX from July of the year t to June of the year t+1 (Fama & French, 1993). It is calculated as:

$$SMB = \frac{1}{3}(Small\ value + Small\ natural + Small\ growth) - \frac{1}{3}(Big\ value + Big\ natural + Big\ growth) \quad (9)$$

Whereas Fama and French (1993) introduce the HML-factor proxy to be similar as SMB, mimicking the risk factor on book-to-market equity, but now this factor proxy considers only two high BE/ME (book-to-market equity) and two low BE/ME portfolios, with approximately the same weighted-average size. Here again the difference of the averages of these high and low portfolio returns is calculated (see Equation 10).

$$HML = \frac{1}{2}(Small\ value + Big\ value) - \frac{1}{2}(Small\ growth + Big\ growth) \quad (10)$$

According to Carhart (1997), the momentum-factor (MOM) is used as a difference of the equally weighted mean of the companies with the largest returns and the equally weighted mean of companies with the smallest returns over a period of eleven-month lagged one month. He also states that these kinds of portfolios are also re-created monthly and are consisting of all NYSE, NASDAQ and Amex stocks. This factor was simply added among the other factors because there appeared to be a tendency of the securities to continue to outperform/underperform in the market over three to 12 months (Jegadeesh & Titman, 1993). The momentum factor can be calculated as:

$$MOM = \frac{1}{2}(Small\ high + Big\ high) - \frac{1}{2}(Small\ low + Big\ low) \quad (11)$$

3.4 Portfolio construction

As already covered in the chapter 3.1 Data, several lists and ratings are used to select interesting target companies for the study. The daily stock prices of different growth and value companies are collected from the period of 2 November 2016 - 26 February 2021, and the companies are grouped into growth companies with low ESG risk (Growth Low), value companies with low ESG risk (Value Low), growth companies with high ESG risk (Growth High), and value companies with high ESG risk (Value High). It is decided to include 40 stocks in each portfolio since otherwise there would be too little assets in each portfolio to diversify efficiently and, thus, the allocation of the assets would not be even. According to Statman (1987), no less than 30 stocks make a well-diversified portfolio which makes it important to understand that diversification is a key tool in reducing the costs, at least until the marginal benefits exceed the marginal costs. Until this point, diversification should be increased.

The different selected weights of Growth Low, Value Low, Growth High, and Value High are 50%, 60%, and 40%, depending on each portfolio. In the expected return formula of the portfolios, used weights for each daily return of each asset are calculated by using the 1/N rule. This rule allocates 1/N to each of the N assets based on the selected weight of the total share of the assets in the portfolio (Garlappi, DeMiguel & Uppal, 2005). For instance, if 60% of the Growth Low stocks are selected in the portfolio, a weight of 1/24 [1/(0.6x40)] is multiplied with each of the Growth Low stock returns in the expected portfolio return formula. As a result, the expected portfolio returns are the sum of each allocated daily returns of the stocks included in the portfolio (see Equation 12).

$$E(r_p) = \sum_{i=1}^{40} w_i r_i \tag{12}$$

Where w_i is the weight of the asset (calculated with 1/N rule) and r_i is the daily return of the stock.

The studied portfolios are constructed as follows (see Table 2). The first six portfolios are consisting of equal amount of two different company groups (see chapter 3.1 Data). These portfolios are also called as the main portfolios since they represent certain important feature. The features are low ESG risk, high ESG risk, growth companies and value companies. The portfolios can be seen representing certain feature since with the equal weights, they neutralize the other aspect. For instance, since Growth portfolio includes equal number of companies with low and high ESG risk, the risk is neutralized in this portfolio which makes it a portfolio representing the growth companies. The two last main portfolios are mixtures of these features. Blend 1 is consisting of growth companies with low ESG risk and value companies with high ESG risk equally, whereas Blend 2 is consisting of value companies with low ESG risk and growth companies with high ESG risk equally. The rest of the portfolios are adjusted portfolios based on the main portfolios. These portfolios are constructed beside the main portfolios since with these portfolios, it can be observed how the main portfolios behave when either the ESG risk is increased or decreased, or when the share of growth/value companies is increased/decreased in the portfolio. The weights are either 60% or 40% in the adjusted portfolios, 60% representing majority of the company group, and 40% representing minority of another company group.

Table 2. Weights of the constructed portfolios

Portfolios	Growth Low	Value Low	Growth High	Value High
Low Risk	50 %	50 %		
High Risk			50 %	50 %
Growth	50 %		50 %	
Value		50 %		50 %
Blend 1	50 %			50 %
Blend 2		50 %	50 %	
Adjusted Low Risk 1	60 %	40 %		
Adjusted Low Risk 2	40 %	60 %		
Adjusted High Risk 1			60 %	40 %
Adjusted High Risk 2			40 %	60 %
Adjusted Growth 1	60 %		40 %	
Adjusted Growth 2	40 %		60 %	
Adjusted Value 1		60 %		40 %
Adjusted Value 2		40 %		60 %
Adjusted Blend 1.1	60 %			40 %
Adjusted Blend 1.2	40 %			60 %
Adjusted Blend 2.1		60 %	40 %	
Adjusted Blend 2.2		40 %	60 %	

Table 2 exhibits how the constructed portfolios are built with different company groups. Here, Growth Low refers to growth companies with low ESG risk, Value Low refers to value companies with low ESG risk, Growth High refers to growth companies with high ESG risk, and Value High refers to value companies with high ESG risk. The portfolios presented in black are representing the main portfolios, where the portfolios presented in grey are representing the adjusted main portfolios.

3.5 Methodology

As presented in the chapter 2.4 Evaluation methods, the methodology in this paper covers the one-factor CAPM (with Jensen's performance index), Fama-French three-factor model, Carhart four-factor model as multi-factor models, and other performance ratios: Sharpe ratio, Treynor's performance index, and Information ratio.

Over time, many researchers have used the one-factor CAPM in individual stock return estimation. The power of this model comes from the linear relation between the risk (beta) and the expected return where the high return is linked to relatively high beta. However, the only risk measure of this model is the risk in shape of beta (Markowitz, 1952). Many studies stress about the shortcomings of CAPM which further show that for the portfolio return estimation, it is more worthwhile to use Fama-French three-factor model (Bartholdy & Peare, 2005). As already mentioned in the chapter 2.4 Evaluation methods, the model added size and value premium to the market risk factor, which makes the portfolio to adapt better with the portfolio return variation (Fama & French, 1993). This change made it more possible to explain the changes in the pace stock return. Whereas, as one of the missing features of Fama-French three-factor model was the difference of the equally weighted mean of the companies with the largest returns and the equally weighted mean of companies with the smallest

returns over a period of eleven-month lagged one month, (Carhart, 1997) introduced the four-factor model with the additional momentum-factor. However, as Liu (2012) suggest, the momentum dynamics can be produced already with the Fama-French three-factor model. In this study, the momentum factor is still important in order to obtain the sensitivities of the portfolios and to observe explanatory power of the other factors when an additional factor is added to the model.

In each of the factor models applied in this study, a simple regression is used to estimate the beta and alpha (risk exposure coefficients) for each of the factors. Here, the dependent variable is the portfolio's excess return, and the independent variables are RMRF (the market risk-factor) SMB risk factor (size premium), HML risk factor (value premium) and/or MOM (momentum factor), however depending on the factor model which is used. As already presented in more detail in chapter 3.3 Benchmarking and factor mimicking portfolios, these factors are obtained from the Kenneth R. French data library. When interpreting the results of the run factor-model regressions, the alpha values are important in determining the outperformance or underperformance of the studied portfolios. When the alpha is significant and positive, it can be observed that the investment is managed remarkable well (Zopounidis, 2002).

Additionally, Sharpe ratio, Treynor's performance index and Information ratio were computed for each of the portfolios. The power and comparability of these models are based on many aspects they cover. Sharpe ratio considers the volatility of the investment, Treynor's performance index considers systematic risk, where Information ratio is based on the link between the alpha and tracking error. The more specific mathematical equations of these models can be investigated in the chapter 2.4 Evaluation methods. When interpreting the results of Sharpe ratio, Treynor's performance index and Information ratio, the higher the measure is, the better is the performance of the investment (Morningstar, 2017).

4. DIAGNOSTIC TESTING

This chapter outlines and describes the diagnostic tests computed for the time-series data used in this research. In more detail, the stationarity is executed with Augmented Dickey-Fuller test, heteroscedasticity is executed with Breusch-Pagan test, and autocorrelation is executed with Durbin-Watson (DW) test. Normality and multicollinearity are examined by computing skewness and kurtosis, and matrix of correlations for the data respectively.

Assumptions and violations

There are five assumptions when it comes to the linear regression model, specifically how the unobservable errors or u_t are generated. According to Brooks (2019), It is assumed that the mean of the errors is zero (Equation 13), there is a finite and constant variance of the errors of all the values of x_t (Equation 14), the errors are independent (Equation 15), the error and x variate are not associating (Equation 16) and that the error is normally distributed (Equation 17). If one or more of these assumptions are violated, it can lead to biased OLS-results. Usually, the problems of the violations arise from wrong coefficient estimates, wrong standard errors associating the model or inappropriate distributions for the test statistics (Brooks, 2019).

$$E(u_t) = 0 \tag{13}$$

$$var(u_t) = \sigma^2 < \infty \tag{14}$$

$$cov(u_i, u_j) = 0 \tag{15}$$

$$cov(u_t, x_t) = 0 \tag{16}$$

$$u_t \sim N(0, \sigma^2) \tag{17}$$

Stationarity

In time-series analysis, one of the first concepts to be examined is whether the series is stationary or not. If the series is not stationary, it can have remarkably biased influence on the properties of the research. Brooks (2019) refers that when testing for stationarity, the observation is in constant autocovariance, constant mean and constant variance. In this paper, the stationarity is tested with Augmented Dickey-Fuller (ADF) test which can also be called the unit root test. The significance of the test is determined in three levels, 10%, 5% and 1%, where the used critical levels are -2.57, -2.86, and -3.43 respectively (Brooks, 2019). If the null hypothesis of the ADF test is rejected, there is no unit root in the time series data. The results of the ADF test for the variables (see Appendix 3) indicate

that for all the data series, the null hypothesis of unit root can be rejected, addressing stationarity (see also Appendix 2). Hence, the stationary data can be used in the further regression.

Heteroscedasticity

Assumption of homoscedasticity means that the variance of the errors needs to be constant in order to fulfill the requirement for linear regression. Whether the time series data is homoscedastic or not, it can be tested for instance with Breusch-Pagan test. This test avoids repeated calculations when obtaining maximum likelihood estimates, and instead computes two OLS-regressions (Breusch & Pagan, 1979). The null hypothesis of this test states homoscedasticity. In this paper, the Breusch-Pagan test is computed for all the studied portfolios per regression. As the p-values of the Breusch-Pagan test for the error terms of the certain portfolios state, in the CAPM, the error terms of Portfolios Low Risk, High Risk, Adjusted Low risk 1, Adjusted Low Risk 2, Adjusted high risk 1 and Adjusted High risk 2 are homoscedastic, in the 3-factor model, the error terms of Portfolios Low Risk, Adjusted Low risk 1, Adjusted Low Risk 2, Adjusted Value 2, Adjusted Blend 1.2 and Adjusted Blend 2.1 are homoscedastic, and in the 4-factor model, the error terms of Portfolios Low Risk, Blend 2, Adjusted Low risk 1, and Adjusted Blend 2.1 are homoscedastic. All the rest error terms were heteroscedastic.

Autocorrelation

It is also assumed, that the error terms are not correlated with each other. But if they are, one can say that the error terms are autocorrelated. Different tests to examine autocorrelation can be computed, but one of the common ones is the Durbin-Watson (DW) test. As Brooks (2019) states, this test is used to test the first-order autocorrelation which means that it considers only the error and its previous value. Brooks (2019) also emphasizes that when interpreting the results of the DW test, the range of the DW statistics limits between zero and four, where zero corresponds to a perfect positive autocorrelation of the residuals and four corresponds to a perfect negative autocorrelation of the residuals. When the DW statistics is near to two, there is little or no autocorrelation existing (Brooks, 2019). DW test is used in this paper to study the existence of autocorrelation of the portfolio data per regression. As Appendix 5 states, autocorrelation is observed only for portfolio Adjusted Growth 2 in all the three models. Both heteroscedasticity and autocorrelation are corrected by using the Newey-West estimator. This procedure modifies the standard errors so they can allow for heteroscedasticity and/or autocorrelation in the used model (Brooks, 2019).

Normality

Another assumption is that the error term is normally distributed. If the term is not normally distributed, it does not follow Gaussian distribution. In normal distribution, the third and fourth moments, skewness and kurtosis are respectively zero and three (Brooks, 2019). However, for sample including large number of observations, skewness, and kurtoses under two and seven respectively still confirm normality (Kim 2013). In this research normality is tested by computing the skewness and kurtosis of the residual data sets. As the results indicate (see Appendix 6), in all the models the error terms of the portfolios High Risk, Blend 1, Adjusted high risk 1, Adjusted High risk 2, Adjusted Growth 2, Adjusted Value 1, and Adjusted Blend 1.1 are non-normal, and in the CAPM and Carhart four-factor model additionally, the error terms of the portfolio Value are non-normal. However, as in this study the sample size is sufficiently large, non-normality is not necessarily a problem. Here the central limit theorem can be followed, and it can be assumed that even if there is absence of error normality, the test statistics will follow normal distribution (Brooks, 2019).

Multicollinearity

The last assumption focused is that the explanatory variables of the linear regression estimation should not be correlated with each other. The problem of highly correlated explanatory variables is called multicollinearity. One way to detect multicollinearity is to set the individual variables in the matrix of correlations (Brooks, 2019). Vilhelmsson (2019) explains that if the correlation between two variables is above 0.8, near multicollinearity is present. In this research normality is tested by using the matrix of correlations, and as the table indicates (see Appendix 7), multicollinearity is not a problem when considering the used explanatory variables.

5. RESULTS AND ANALYSIS

This chapter discloses the main results generated by the methods and models used. In more detail, first the descriptive statistics of the constructed portfolios is presented, then a short description of the results of the computed Sharpe ratio, Treynor's performance index and Information ratio is stated. The chapter continues with performance results and analysis of the different factor models, specifically the one-factor Capital Asset Pricing model, Fama-French three-factor model and Carhart four-factor model.

5.1 Descriptive statistics

The descriptive statistics of the constructed portfolios is introduced in Table 3. By focusing on the main portfolios representing certain ESG risk, value/growth stocks or blends of all aforesaid, it can be observed in general that when considering only the descriptive statistics, the portfolio with low ESG risk generates higher mean return than the portfolio with high ESG risk, the portfolio representing growth stocks generates higher mean return than the portfolio representing value stocks, and the portfolio consisting of value stocks with low ESG risk and growth stocks with high ESG risk equally generates higher mean return than the portfolio representing growth stocks with low ESG risk and value stocks with high ESG risk equally. Nevertheless, out of all these main portfolios, the portfolio representing growth companies generates the highest mean daily return, whereas the portfolio representing value companies generates the lowest. When focusing only on the adjusted portfolios where the two company groups included are not equal anymore, the portfolio representing growth companies, specifically with majority of high ESG risk can be seen generating the highest mean daily returns, whereas the portfolio representing value companies with majority of low ESG risk can be seen generating the lowest mean daily returns. Out of all the constructed portfolios, the same portfolios perform the best and the worst as in the case of only the adjusted portfolios.

The standard deviations are relatively low for all the portfolios but for the portfolio representing low risk with majority of value companies (Adjusted Low Risk 2), and for the portfolio representing growth companies with majority of high ESG risk (Adjusted Growth 2), it is above 4%. When the standard deviation is higher, it means that the values are further away from the mean which can be also seen from the range of the maximum and minimum daily returns of the portfolios. The low ESG risk portfolio with majority of value companies (Adjusted Low Risk 2) can also be observed having the widest range between the highest and the lowest daily returns. When it comes to the difference between the means and medians of the portfolios, since the difference is the largest for the portfolio representing growth companies with majority of high risk (Adjusted Growth 2), its daily returns are

the least evenly distributed from the lowest daily returns to the largest. On the other hand, the difference between the mean and median of the daily returns is the smallest for the portfolio with majority of value companies with low ESG risk and minority of growth companies with high ESG risk (Adjusted blend 2.1) It can be then concluded that for this portfolio, the daily returns were the most evenly distributed from the lowest daily return to the highest.

Table 3. Descriptive statistics of the constructed portfolios

Portfolios	No. Of stocks	Mean	St. Dev	Max	Min	Median
Low Risk	40	0.157 %	2.799 %	19.771 %	-25.074 %	0.251 %
High Risk	40	0.138 %	3.096 %	23.956 %	-28.977 %	0.247 %
Growth	40	0.261 %	3.116 %	20.986 %	-28.278 %	0.423 %
Value	40	0.037 %	2.990 %	22.756 %	-27.664 %	0.134 %
Blend 1	40	0.131 %	2.954 %	23.087 %	-26.418 %	0.264 %
Blend 2	40	0.154 %	2.811 %	18.825 %	-28.864 %	0.232 %
Adjusted Low Risk 1	40	0.162 %	2.813 %	19.850 %	-25.689 %	0.269 %
Adjusted Low Risk 2	40	0.291 %	5.790 %	42.671 %	-56.034 %	0.529 %
Adjusted High Risk 1	40	0.139 %	3.082 %	24.758 %	-28.884 %	0.255 %
Adjusted High Risk 2	40	0.137 %	3.045 %	22.679 %	-29.128 %	0.305 %
Adjusted Growth 1	40	0.254 %	3.107 %	20.974 %	-28.068 %	0.458 %
Adjusted Growth 2	40	0.501 %	4.053 %	26.140 %	-32.480 %	0.839 %
Adjusted Value 1	40	0.035 %	3.030 %	22.390 %	-28.598 %	0.142 %
Adjusted Value 2	40	0.036 %	2.918 %	21.879 %	-25.380 %	0.118 %
Adjusted Blend 1.1	40	0.139 %	3.028 %	24.291 %	-27.934 %	0.273 %
Adjusted Blend 1.2	40	0.129 %	2.884 %	21.919 %	-25.491 %	0.267 %
Adjusted Blend 2.1	40	0.150 %	2.873 %	19.073 %	-28.013 %	0.218 %
Adjusted Blend 2.2	40	0.163 %	2.871 %	20.800 %	-27.319 %	0.241 %

Table 3 presents the daily return characteristics of the constructed portfolios covering the whole period from 2 November 2016 to 26 February 2021. The table indicates the number of the stocks included in the portfolio, mean, standard deviation, maximum, minimum and median of the daily returns of each portfolio. The proxy used in this table is the yield of the portfolio returns. The portfolio weights can be observed from Table 2. The portfolios presented in black are representing the main portfolios, where the portfolios presented in grey are representing the adjusted main portfolios.

5.2 Performance results

In this section, a comparison of the performances of the different portfolios is carried out. First, the performance is studied with models that do not consider additional factors to give a general overview of the results in shape of Sharpe ratio, Treynor's performance index and Information ratio. Then the portfolios are studied in more detail with the Capital Asset Pricing model, Fama-French three-factor model, and Carhart four-factor model.

5.2.1 Performance ratios

The results of the performed Sharpe ratio, Treynor's performance index and Information ratio can be observed from Table 4. Since the Capital Asset Pricing model covers Jensen's performance index, is not covered in this performance measure section. As already revealed, the higher the measure of these performance ratios (applied to all the measures), the better is also the performance of the target portfolio (see chapter 2.4 Evaluation methods).

The results of all the three ratios are mirroring each other's results nearly, especially when looking at the top performing and the least well performing portfolios. When first interpreting the results of the main portfolios, it can be observed in general that the portfolio representing low ESG risk outperforms the portfolio representing high ESG risk, the portfolio representing growth outperforms the portfolio representing value, and the portfolio consisting of value companies with low ESG risk and growth companies with high ESG risk equally outperforms the portfolio consisting of growth companies with low ESG risk and value companies with high ESG risk equally. However, it can be observed that out of all the main portfolios, the portfolio including growth companies generates the highest measure in all the models. The second-best performing portfolio represents low ESG risk, and the worst performing portfolio represents value companies.

When comparing the performances of the adjusted portfolios with the the main portfolios, it can be noticed that growth seems to still outperform value since out of all the adjusted portfolios, the growth portfolio with majority of high ESG risk (Adjusted Growth 2) performs the best where the value portfolio with majority of low ESG risk (Adjusted value 1) seems to be the worst performing one. According to Information ratio, the worst performing adjusted portfolio is however the value portfolio with majority of high ESG risk (Adjusted Value 2). Out of all the constructed portfolios, the growth portfolio with high ESG risk is the best performing where according to Sharpe ratio and Treynor's performance index, the value portfolio with majority of low ESG risk seems to be the worst performing.

Table 4. Results of the performance ratios

	Performance ratios		
Portfolio	SR	TR	IR
Low Risk	0.056	0.074	0.009
High Risk	0.045	0.062	-0.017
Growth	0.084	0.116	0.083
Value	0.012	0.018	-0.088
Blend 1	0.044	0.060	-0.023
Blend 2	0.055	0.073	0.005
Adjusted Low Risk 1	0.058	0.076	0.015
Adjusted Low Risk 2	0.050	0.066	-0.017
Adjusted High Risk 1	0.045	0.062	-0.017
Adjusted High Risk 2	0.045	0.062	-0.019
Adjusted Growth 1	0.082	0.113	0.080
Adjusted Growth 2	0.124	0.294	0.111
Adjusted Value 1	0.011	0.016	-0.085
Adjusted Value 2	0.012	0.017	-0.088
Adjusted Blend 1.1	0.046	0.062	-0.019
Adjusted Blend 1.2	0.045	0.061	-0.021
Adjusted Blend 2.1	0.052	0.070	-0.002
Adjusted Blend 2.2	0.057	0.076	0.012

Table 4 exhibits the results of Sharpe ratio, Treynor's performance index and Information ratio. Here, SR refers to Sharpe ratio, TR refers to Treynor's performance index and IR refers to Information ratio. The mathematical equations are covered in the chapter 2.4 Evaluation methods. The portfolios presented in black are representing the main portfolios, where the portfolios presented in grey are representing the adjusted main portfolios.

5.2.2 Factor models

Capital Asset Pricing Model, Fama-French three-factor model and Carhart four factor model were estimated for all the constructed portfolios. The results of these models are illustrated in Table 5 and Appendix 8. It can be noticed from the tables that the results are close between all the models, however differing slightly.

Capital Asset Pricing model

As already mentioned, the alpha of the factor models is Jensen's performance index. This value is remarkable when assessing the performances of different portfolios. In the estimated CAPM, only alphas for the main portfolios Growth and Value are significant, whereas they are significant only for the adjusted portfolios Growth 1, Growth 2, Value 1, and Value 2. Important noticing is that among many positive alphas, many of the portfolios generated negative alphas. This means that these portfolios are unprofitable.

When only considering the alpha values of the main portfolios, it is clear that the portfolio with low risk performs better than the portfolio with high risk, the portfolio with growth stocks outperforms

the portfolio with value stocks, and the portfolio consisting of value companies with low ESG risk and growth companies with high ESG risk equally performs better than the portfolio consisting of growth companies with low ESG risk and value companies with high ESG risk equally, which is also visible from the performance ratios. Out of the main portfolios, the portfolio representing growth companies performs the best, where the portfolio representing value companies performs the worst. When focusing only on the adjusted portfolios, the growth portfolio with majority of high ESG risk can be seen performing the best, where the value portfolio with majority of low ESG risk can be observed performing the worst. All in all, the growth portfolio with majority of high ESG risk generates the highest significant alpha among all the portfolios i.e., it gains the highest significant excess returns, whereas the value portfolio with majority of low ESG risk generates the lowest.

When it comes to the market betas (RMRF), it is significant for all the portfolios, and the low ESG risk portfolio with majority of value stocks (Adjusted Low Risk 2) seems to be the most sensitive to the market. Anyway, the exposure to the market seemed to be narrow between all the portfolios which is also visible fom the R squared values, and in case of all the portfolios, it is closer to one than zero. This means that the model has power to explain the return variation. As an exception however, the R squared value of the growth portfolio with majority of high ESG risk (Adjusted Growth 2) is relatively low compared to the other portfolios.

Fama-French three-factor model

The results of the Fama-French three-factor model are mirroring distinctly to the results of the CAPM (see Table 5 and Appendix 8). The same portfolios are significant, and the same performance order between the main portfolios can be perceived except according to the results of the three-factor model the portfolio including value companies with low ESG risk and growth companies with high ESG risk equally (Blend 2) can be seen performing better than the low ESG risk portfolio which is the other way around in the CAPM. When it comes to the adjusted portfolios, the same portfolio is performing the best as in the CAPM but now the value portfolio with majority of high ESG risk can be seen performing the worst which makes it also the worst performing portfolio of all the constructed portfolios. The market factor (RMRF) is still positive for all the portfolios and narrow between their values. Additionally, the low ESG risk portfolio with majority of value stocks (Adjusted Low Risk 2) is still the most exposed to the market excess return.

When adding two additional factors to the CAPM, new information appeares. It can be observed that SMB (size premium) and HML (value premium) are significant for all the portfolios. As the size factor is positive for all the portfolios, it can be interpreted that there is a positive exposure to the

small company risk factor, yet to the size effect for all the portfolios. Whereas when looking at the value factor, there appear both negative and positive exposures for this factor. It can be observed that the portfolios including more value stocks are more exposed to the value factor than those portfolios with less value stocks. For instance, Adjusted Value 1 (value portfolio with majority of low ESG risk) is the most exposed to the value factor, whereas Adjusted Growth 2 (growth portfolio with majority of high ESG risk) can be seen being the least exposed. In this model, the R squared value for all the portfolios is slightly higher than in the CAPM which indicates that this model has more explanatory power than CAPM. Again however, the R squared value is the smallest for the growth portfolio with majority of high ESG risk (Adjusted Growth 2).

Carhart four-factor model

The alphas, market betas, size factor, value factor and R squared values of the Carhart four-factor model are clearly reminding a lot of the results of Fama-French three-factor model, and CAPM. The values are close to each other, and the same portfolios remain significant. Hence, the performance of the portfolios is very close to the previous models, except again as in CAPM, the worst performing portfolio is the value portfolio with majority of low ESG risk (Adjusted Value 1). This however is not surprising since here the same variables are used.

As the momentum factor is now added, the value factor, HML seems to change when comparing to the Fama-French three-factor model. Some of the portfolios are exposed to this factor the opposite way. For instance, in this model it is significant that the exposure of the portfolio including value companies with low ESG risk and growth companies with high ESG risk equally (Blend 2) to this factor is negative, whereas it was positive when the momentum factor was not added yet. Also, for some of the portfolios the exposure to this factor loses its significancy. When it comes to the momentum factor, it is significant for all the portfolios and positive only for the growth portfolio with neutral ESG risk, and for the growth portfolio with majority of low ESG risk (Adjusted Growth 1). As already mentioned above, the R squared values do not react at all or only a bit for the added factor. This means that the momentum factor does not increase the explanatory power meaningfully for this model when compared to the previous model.

Table 5. Results of the factor models

Portfolio	CAPM Alpha	Three-factor Alpha	Four-factor alpha	RMRF	SMB	HML	MOM	Adj R^2
Low Risk	0.002	-0.005	-0.007	2.101***	0.356***	-0.145***	-0.075**	0.932
	(0.023)	(0.022)	(0.022)	(0.018)	(0.036)	(0.036)	(0.029)	
High Risk	-0.025	-0.008	-0.016	2.161***	0.646***	0.260***	-0.236***	0.903
	(0.036)	(0.029)	(0.029)	(0.064)	(0.081)	(0.088)	(0.055)	
Growth	0.098**	0.055*	0.058**	2.279***	0.738***	-0.674***	0.092**	0.908
	(0.037)	(0.029)	(0.029)	(0.043)	(0.072)	(0.07)	(0.052)	
Value	-0.118**	-0.071**	-0.082***	2.009***	0.160***	0.719***	-0.346***	0.936
	(0.04)	(0.025)	(0.023)	(0.046)	(0.054)	(0.07)	(0.046)	
Blend 1	-0.028	-0.016	-0.023	2.124***	0.394***	0.116**	-0.218***	0.906
	(0.032)	(0.028)	(0.027)	(0.053)	(0.067)	(0.093)	(0.065)	
Blend 2	-0.001	-0.002	-0.006	2.091***	0.437***	-0.030	-0.099***	0.937
	(0.023)	(0.022)	(0.022)	(0.017)	(0.035)	(0.035)	(0.028)	
Adj. low risk	0.006	-0.003	-0.005	2.121***	0.340***	-0.168***	-0.042	0.936
	(0.022)	(0.022)	(0.022)	(0.017)	(0.035)	(0.035)	(0.028)	
Adj. low risk 2	-0.026	-0.022	-0.032	4.356***	0.771***	-0.013	-0.306***	0.961
	(0.04)	(0.036)	(0.035)	(0.064)	(0.083)	(0.102)	(0.073)	
Adj. high risk 1	-0.024	-0.008	-0.015	2.160***	0.602***	0.255***	-0.238***	0.905
	(0.035)	(0.029)	(0.028)	(0.067)	(0.079)	(0.09)	(0.057)	
Adj. high risk 2	-0.025	-0.014	-0.020	2.152***	0.610***	0.197***	-0.206***	0.906
	(0.034)	(0.029)	(0.028)	(0.058)	(0.077)	(0.077)	(0.05)	
Adj. Growth 1	0.090**	0.053*	0.054*	2.267***	0.819***	-0.564***	0.063*	0.905
	(0.036)	(0.029)	(0.029)	(0.039)	(0.06)	(0.056)	(0.042)	
Adj. Growth 2	0.376***	0.326**	0.316**	1.730***	1.227***	-1.114***	-0.310**	0.353
	(0.103)	(0.099)	(0.099)	(0.199)	(0.296)	(0.246)	(0.149)	
Adj. Value 1	-0.120**	-0.071**	-0.082***	2.006***	0.188***	0.777***	-0.354***	0.931
	(0.043)	(0.026)	(0.024)	(0.05)	(0.058)	(0.081)	(0.056)	
Adj. Value 2	-0.116**	-0.071**	-0.081***	1.960***	0.174***	0.688***	-0.335***	0.932
	(0.039)	(0.024)	(0.023)	(0.042)	(0.054)	(0.066)	(0.045)	
Adj. Blend 1.1	-0.024	-0.013	-0.019	2.187***	0.391***	0.141**	-0.169***	0.907
	(0.032)	(0.028)	(0.028)	(0.057)	(0.07)	(0.105)	(0.069)	
Adj. Blend 1.2	-0.026	-0.017	-0.024	2.078***	0.394***	0.044	-0.216***	0.900
	(0.031)	(0.028)	(0.028)	(0.047)	(0.057)	(0.078)	(0.053)	
Adj. Blend 2.1	-0.006	-0.005	-0.009	2.086***	0.616***	0.072*	-0.122***	0.926
	(0.028)	(0.024)	(0.024)	(0.019)	(0.038)	(0.038)	(0.031)	
Adj. Blend 2.2	0.006	0.002	0.000	2.108***	0.618***	-0.003	-0.076**	0.931
	(0.026)	(0.023)	(0.023)	(0.039)	(0.055)	(0.051)	(0.034)	

Table 5 presents the results of the factor models. The additional factors are from the Carhart four-factor model. The Alpha is the intercept of the model, which can be expressed as Jensen's alpha. RMRF represents the market excess return. SMB represents the size premium, HML represents the value premium, and MOM represents the momentum factor. The first values are the coefficients and the values in the brackets are the standard errors. R^2 estimates represent the explanatory power of the model. The stars represent the significance (p-values), where the risk levels can be 1% (***), 5% (**) or 10% (*). The regressions are run after fixing the heteroscedasticity and autocorrelation with the Newey-West estimator. The number of observations for each of the models is 1086. The portfolios presented in black are representing the main portfolios, where the portfolios presented in grey are representing the adjusted main portfolios.

The results of all the factor models indicate that the difference between the performances of growth and value portfolios is significant. In all the models the ESG risk neutral growth portfolio outperforms

significantly the ESG risk neutral value portfolio. When the ESG risk is changed to lean on either high or low ESG risk for the growth portfolios, it is distinct and significant that when the ESG risk is increased, in other words, majority of the companies included in the growth portfolio are bearing high ESG risk, the performance of the portfolio improves. Whereas, when the ESG risk of the growth portfolio is decreased, in other words, majority of the companies included in the growth portfolio are bearing low ESG risk, the performance of that portfolio declines, however keeping the portfolio in the top three of all the constructed portfolios based on its performance. These interpretations are also confirmed with all the performance ratios.

When it comes to the performance of the value portfolio, its performance is the weakest of all the main portfolios. It depends however on the model how the portfolio acts when increasing or decreasing ESG risk. Both CAPM and Carhart four-factor model (also both Sharpe ratio and Treynor's performance index) state that when ESG risk is decreased, in other words, majority of the companies included in the value portfolio are bearing low ESG risk, the performance of the value portfolio decreases. Whereas, according to Fama-French three-factor model, and all the performance ratios, the performance of the value portfolio decreases when increasing ESG risk in the portfolio. Consequently, all these three value portfolios were in the last three least well performing of all the constructed portfolios.

The rest of the performances of the main portfolios and their adjustments vary insignificantly depending on the model. It is visible however (but not statistically significant according to the factor models) that both the low ESG risk, and high ESG risk portfolios start performing better when the share of growth companies is increased, and the share of value companies is decreased. The effect for both portfolios is the opposite when increasing the share of value companies. In this case, they start performing worse. The performance of the blended portfolios (including both value and growth companies, and high and low ESG risk) is not unambiguous. For the Blend 1 portfolio, it is visible from all the models that when increasing the share of growth companies with low ESG risk and decreasing the share of value companies with high ESG risk, the performance increases. However, all the models did not confirm that the performance of the portfolio would get worse when adding the share of the value companies with high ESG risk and decreasing the share of growth companies with low ESG risk. All the models (also the performance ratios) support each other when it comes to the changes in Blend 2 portfolio. Increasing the share of growth companies with high ESG risk and decreasing the share of value companies with low ESG risk makes the portfolio perform better, where the opposite effect is visible when decreasing the share of growth companies with high ESG risk and

increasing the share of value companies with low ESG risk. These effects again were not significant according to the factor models.

These results tell that the growth/value effect is way stronger than the high/low ESG risk effect when combining these two effects in one portfolio. However, as the best performing portfolio among all the portfolios is the growth portfolio with majority of high ESG risk and the worst performing is the value portfolio with majority of low ESG risk, it can be observed that high ESG risk outperforms the low ESG risk to some extent. When considering the reasons behind the performances of the portfolios, specifically why value companies with low ESG risk are not outperforming growth companies with high ESG risk when considering the return change of the portfolios as the proxy, the reasons can be mirroring to the companies inside the constructed company groups. When comparing company groups Growth High and Value Low, the industries representing these groups are very different. Mostly, companies that fulfill the requirements of Growth High are electrical and medical device manufacturers, biotechnology, and other technology companies. Whereas companies that fulfill requirements of Value Low, are mainly representing steady services, retail, and technology. DiCiurcio *et al.* (2021) emphasize that in the recent years the underperformance of value stocks in the USA is mainly derived from the low inflation rates which is supported by the skepticism of the investors. He stresses also that meanwhile the attractiveness and novelty of the highly growing tech-companies boosts their outperformance and cash flows. Also, as Royal (2020) suggests, one of the reasons for growth stocks' outperformance could be that the large high-tech companies which are more vulnerable for higher volatilities with massive opportunities have had a better change to generate higher returns. However, according to the research of DiCiurcio *et al.* (2021), in years ahead, value stocks are poised to top growth stocks again even if growth stocks would outperform now. The study found that growth trade would be soon overheating since there is observed to be an association between future relative returns and fair value.

Even if the high ESG risk seems to be a component of some outperforming portfolios, Fidelity's (2020) study computed globally during 2020 shows that even the global pandemic did not affect the outperformance of the ESG investments amid volatility. This study showed that even if the markets fell, the companies with top ESG rating scale outperformed the companies with lower ESG scale in 11 out of the 12 months. One of the reasons of such performance according to the study is that the investments reacted less intense to the changes as the market, which means that these investments are not that vulnerable to volatility. To conclude, when comparing the previous studies computed for investments with different ESG risks to this study where the two aspects are combined, ESG risk as

one of them, it can be stated that the combining effect emphasizes the growth/value effect and does not directly advocate the performance of investments with certain level of ESG risk.

6. CONCLUSION

The previous research has confirmed repeatedly that value stocks tend to outperform growth stocks over time. This claim has been evidenced *inter alia* by Fama and French (1998), Lakonishok, Shleifer and Vishny (1994) and Davis (1994). Whereas studies carried out about the performance of investments that can be considered sustainable have proven that over time they tend to outperform the investments that are seen being irresponsible to some extent. This has been evidenced *inter alia* by Serafeim (2014) and Friede, Busch and Bassen (2015). Since there is little or no showing about performance of stock portfolios covering these two aspects, the research investigates performance of fictive constructed portfolios with different weights of selected US growth and value stocks covering both high and low ESG risk. Thus, with reference to the previous studies, it could be assumed that value investments with low ESG risk would be the ones that perform the best in the market.

With regards to the above, the research aims to answer the following question:

By combining the previously proved outperforming aspects of growth/value investments, and investments with certain ESG level, can value portfolio representing low ESG risk be seen performing the best among all the constructed portfolios?

The study arrives at contradicting results for the combined performance of the constructed portfolios. The results of the factor models, supported by the performance ratios show that in the time-period between 2 November 2016 and 26 February 2021, when using the daily return yield as the proxy and when only considering the alpha values of the main portfolios, it is clear that the portfolio with low ESG risk performs better than the portfolio with high ESG risk, the growth portfolio outperforms the value portfolio, and the portfolio representing value companies with low ESG risk and growth companies with high ESG risk equally performs better than the portfolio representing growth companies with low ESG risk and value companies with high ESG risk equally, which is also visible from the performance ratios. This performance order is not notably significant.

However, the difference between the performances of growth and value portfolios is significant. The results emphasize that the ESG risk neutral growth portfolio outperforms significantly the ESG risk neutral value portfolio. When the ESG risk is changed to lean on either high or low risk for the growth portfolio, it is distinct and significant that when the ESG risk is increased, the performance of the portfolio improves. On the other hand, when the ESG risk of the growth portfolio is decreased, the performance of this portfolio declines. Most of the results also indicate that when the ESG risk is decreased in the value portfolio, the performance of the value portfolio also decreases. It is not however unambiguous that the risk would have significant influence on the value portfolio and its

performance since some of the results indicate that whether the value portfolio represents high or low ESG risk, it still performs worse than the value portfolio with neutral ESG risk. All in all, it is statistically significant that the best performing portfolio according to all the results is the growth portfolio with majority of high ESG risk and the worst performing is the value portfolio with majority of low ESG risk. With regards to the above, it can be concluded that the growth/value effect is way stronger than the high/low ESG risk effect when combining these two effects in one portfolio, but high ESG risk can be seen outperforming low ESG risk to some extent, especially when it comes to the performance of the growth portfolio.

As one of the biggest limitations of this study, the time-period can be considered being relatively narrow. The performance of the constructed portfolios can potentially differ with different time-periods. However, since the attributes of the companies live, it is important for this kind of study that the attributes remain the same throughout the whole study period which can be considered challenging if the time-period is relatively long. Another limitation that can have effect on the outcome of this study is the portfolio construction. With more versatile and even more drastic portfolio weights, the performance order might differ. For the future, it would be interesting to study the same associations with larger sample. Longer time-period might be challenging regarding the associations of this study, yet the data would be more comprehensive. Also, for the future studies in the field of value/growth companies with different ESG risks, it would be beneficial to cover other asset classes than only stocks in the study. Another suggestion for the future researchers is that the reasons behind the best/worst performing portfolios would be necessary to find out with different proxies of quality measures of the companies included in the portfolios.

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APPENDICES

Appendix 1. Daily return characteristics per year

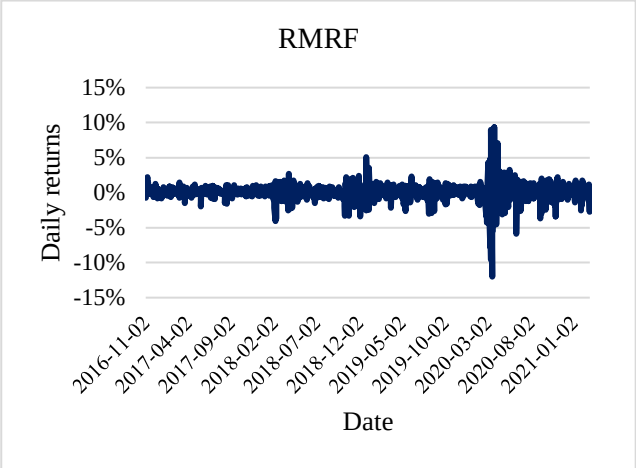
Growth Low							
Year	Companies	Mean	St. Dev.	Skewness	Kurtosis	Max	Min
2016	24	0.04 %	2.15 %	1.778	25.200	26.09 %	-12.08 %
2017	24	0.18 %	1.78 %	1.146	23.278	21.41 %	-20.94 %
2018	24	0.04 %	2.37 %	-0.510	9.610	19.77 %	-22.95 %
2019	24	0.15 %	2.08 %	-1.241	23.257	20.73 %	-31.45 %
2020	24	0.16 %	3.29 %	-0.522	8.908	29.99 %	-29.20 %
2021	24	0.10 %	2.54 %	0.637	3.905	15.15 %	-8.61 %

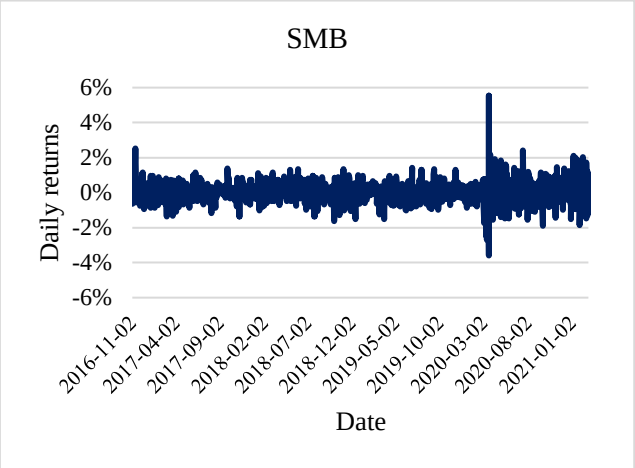
Value Low							
Year	Companies	Mean	St. Dev.	Skewness	Kurtosis	Max	Min
2016	24	0.17 %	1.53 %	0.667	11.112	12.84 %	-8.10 %
2017	24	0.05 %	1.35 %	-0.836	48.801	21.29 %	-26.18 %
2018	24	-0.04 %	1.70 %	-0.191	9.453	22.97 %	-12.17 %
2019	24	0.07 %	1.57 %	-0.126	9.283	17.07 %	-13.70 %
2020	24	-0.02 %	3.32 %	-0.489	9.177	24.58 %	-31.08 %
2021	24	0.17 %	2.56 %	0.202	3.010	15.55 %	-12.25 %

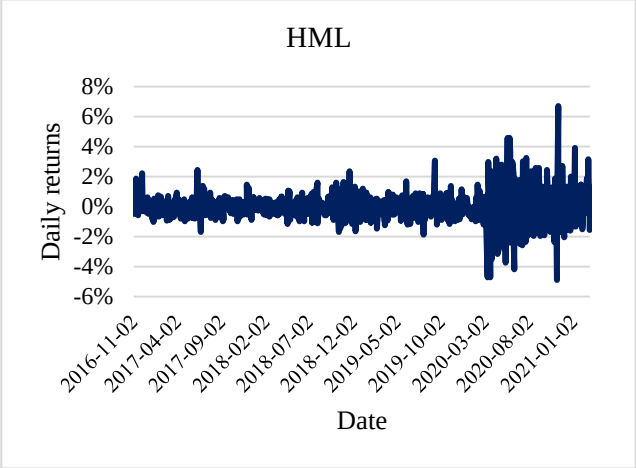
Growth High							
Year	Companies	Mean	St. Dev.	Skewness	Kurtosis	Max	Min
2016	24	0.13 %	2.91 %	0.375	11.508	19.88 %	-21.37 %
2017	24	0.14 %	2.40 %	0.300	40.884	41.68 %	-39.53 %
2018	24	0.00 %	2.74 %	-0.263	12.108	28.43 %	-30.93 %
2019	24	0.16 %	2.46 %	-0.339	23.442	26.25 %	-30.73 %
2020	24	0.22 %	3.75 %	-0.265	8.909	35.38 %	-30.12 %
2021	24	0.12 %	2.96 %	0.193	2.497	15.55 %	-12.25 %

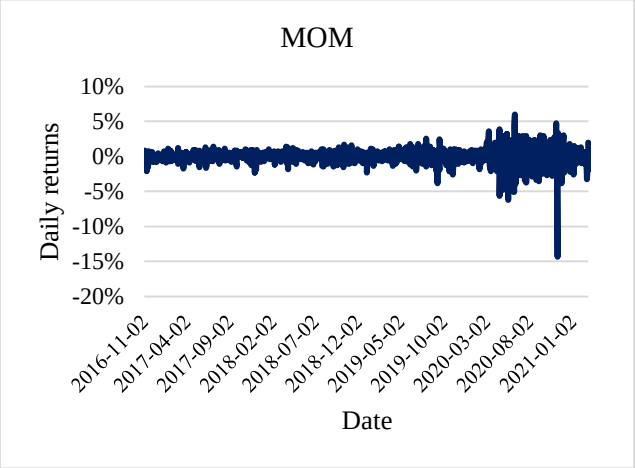
Value High							
Year	Companies	Mean	St. Dev.	Skewness	Kurtosis	Max	Min
2016	24	0.24 %	1.93 %	1.771	14.745	18.90 %	-8.32 %
2017	24	0.04 %	1.32 %	1.032	1.032	25.76 %	-12.87 %
2018	24	-0.04 %	1.69 %	-0.250	4.515	14.44 %	-12.53 %
2019	24	0.03 %	1.65 %	-1.285	28.798	12.85 %	-32.10 %
2020	24	-0.10 %	4.16 %	-2.119	37.217	29.04 %	-76.41 %
2021	24	0.26 %	2.66 %	0.409	2.259	12.31 %	-9.58 %

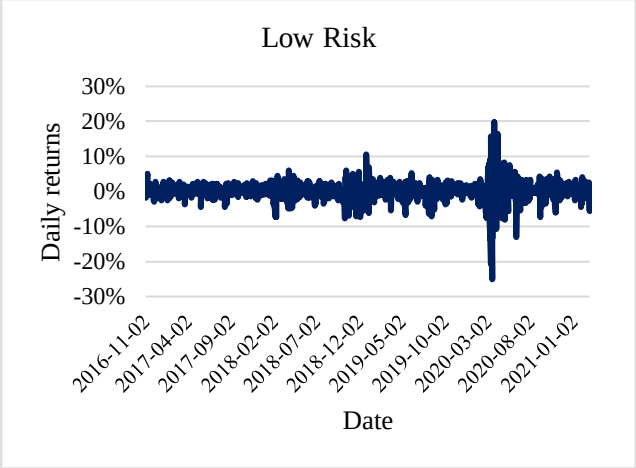
Appendix 2. Daily return plots per variable

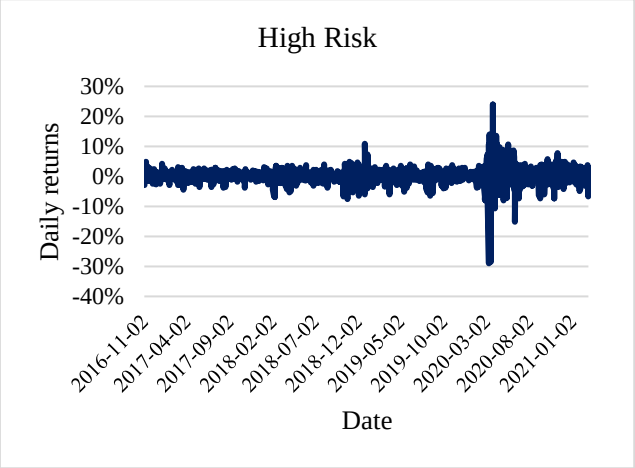


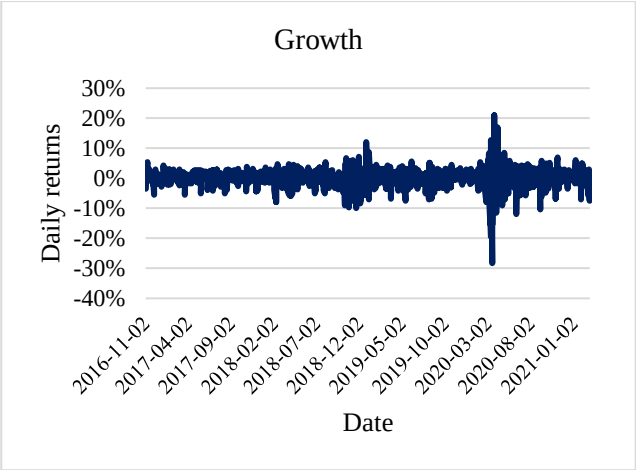








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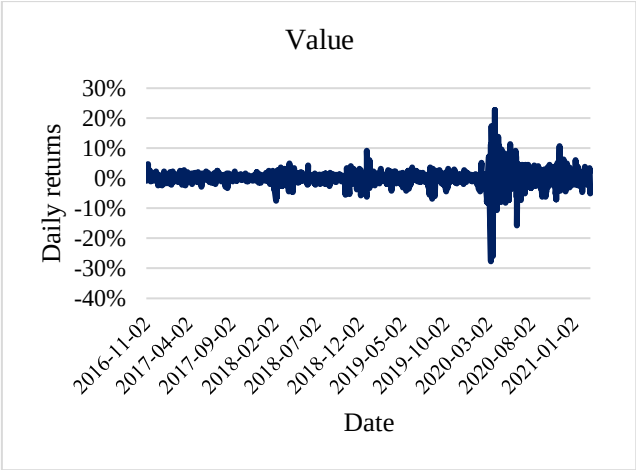
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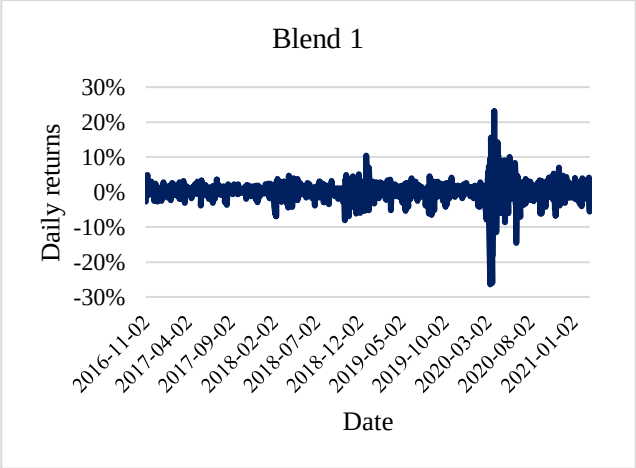
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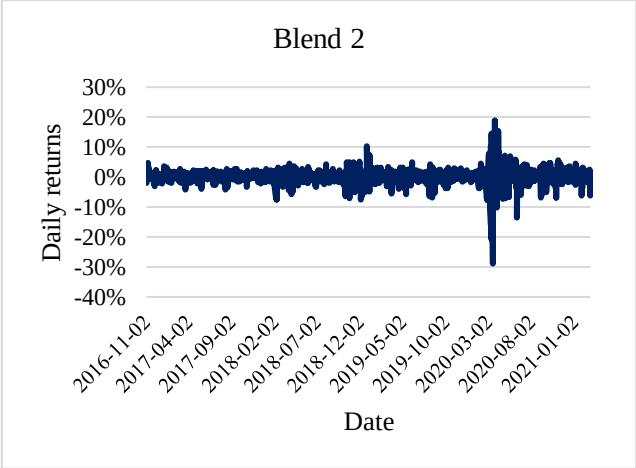
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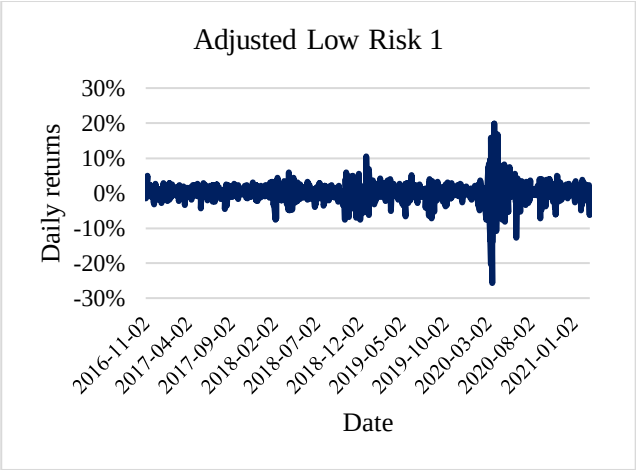
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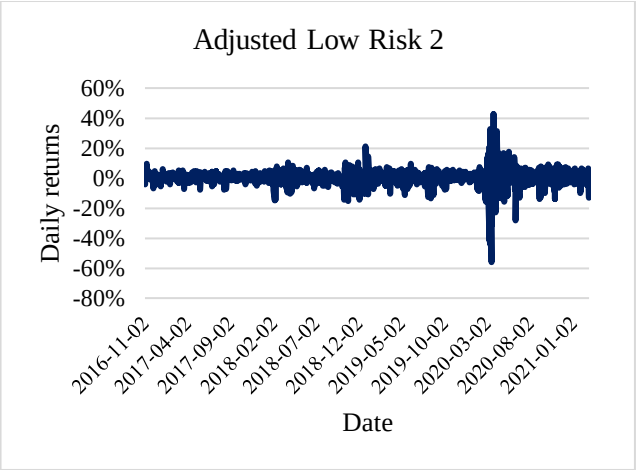
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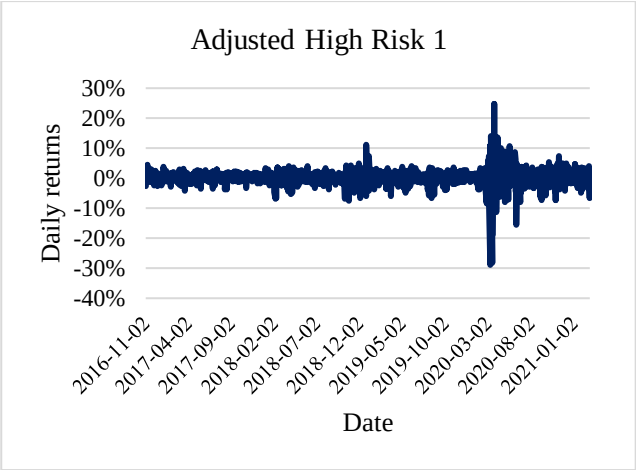
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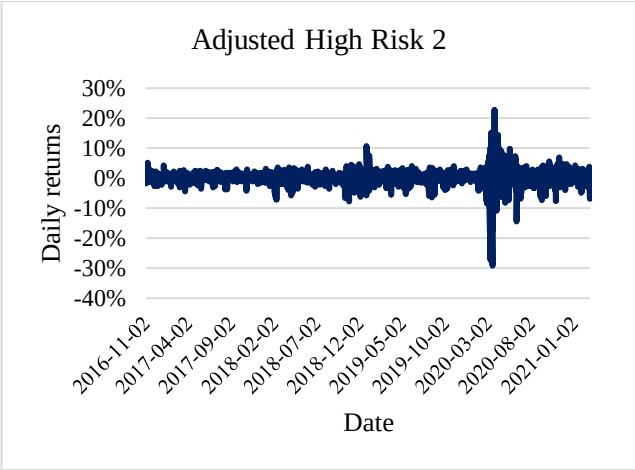
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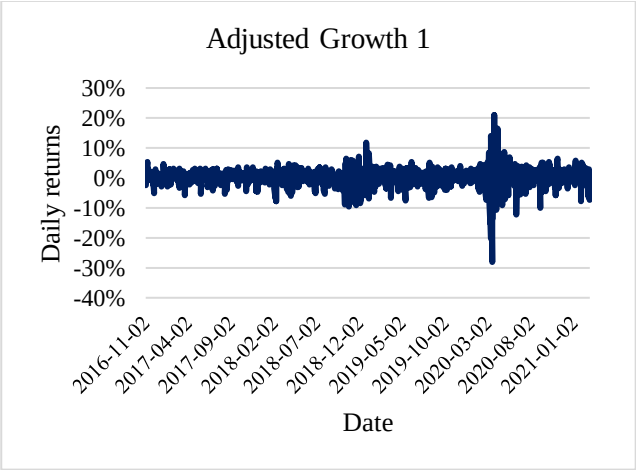
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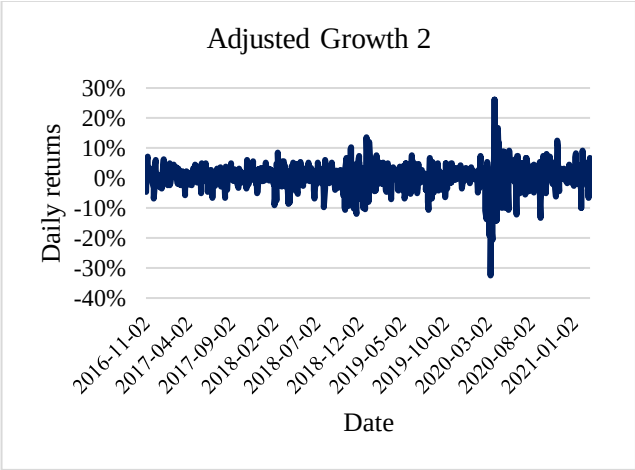
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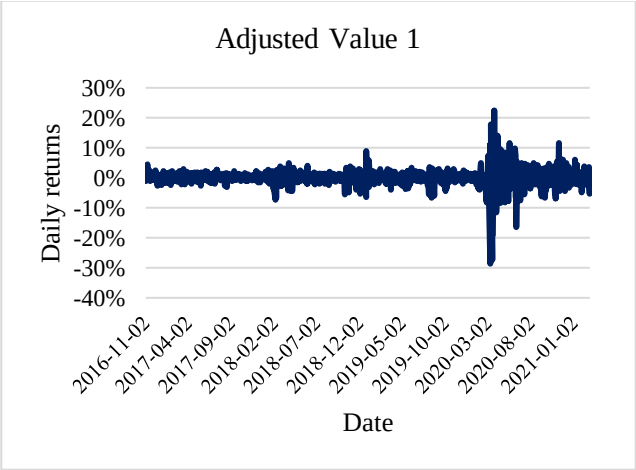
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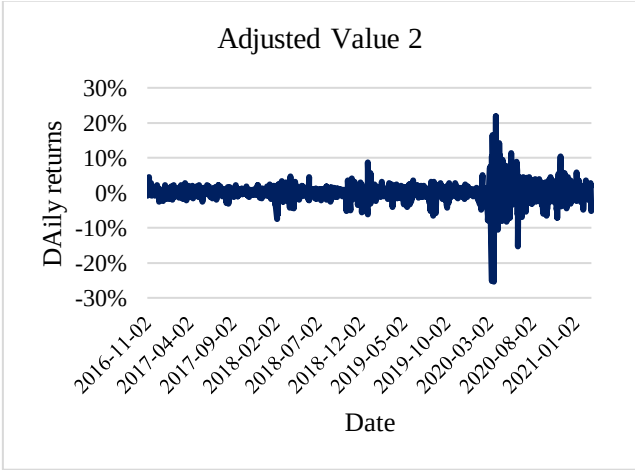
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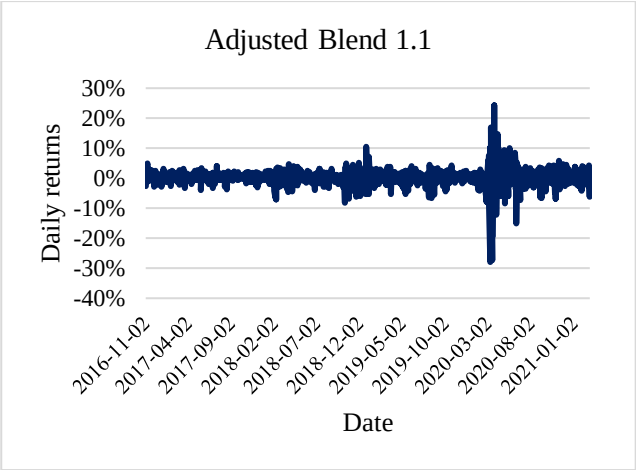
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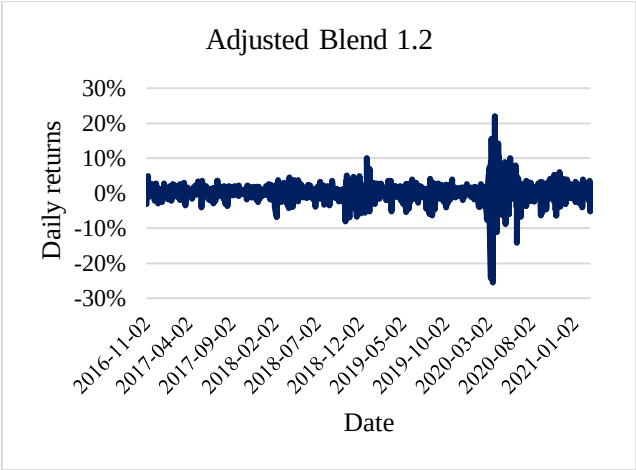
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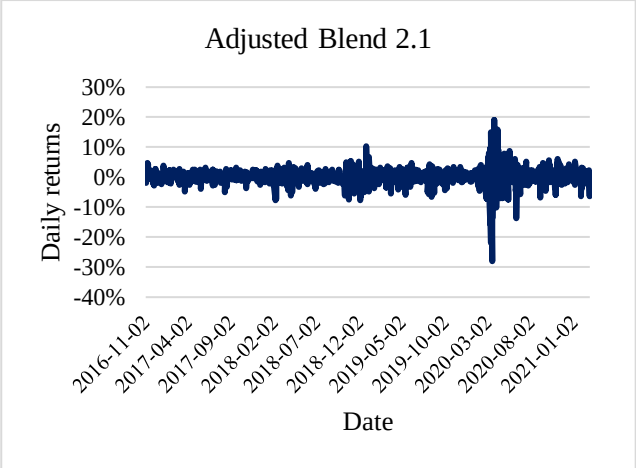
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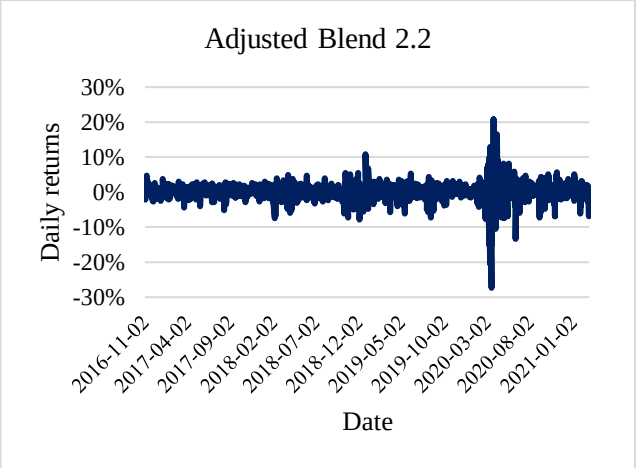
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Appendix 3. Augmented Dickey-Fuller stationarity test for the variables

Augmented Dickey-Fuller	
Variable	Test statistic
RMRF	-22.464
HML	-23.328
SMB	-23.215
MOM	-24.010
Low Risk	-21.642
High Risk	-20.894
Growth	-21.450
Value	-21.237
Blend 1	-21.031
Blend 2	-21.223
Adjusted Low Risk 1	-21.737
Adjusted Low Risk 2	-21.338
Adjusted High Risk 1	-20.962
Adjusted High Risk 2	-20.836
Adjusted Growth 1	-21.559
Adjusted Growth 2	-20.524
Adjusted Value 1	-21.161
Adjusted Value 2	-21.233
Adjusted Blend 1.1	-21.140
Adjusted Blend 1.2	-21.006
Adjusted Blend 2.1	-21.170
Adjusted Blend 2.2	-21.029

Appendix 4. Breusch-Pagan heteroskedasticity test for the portfolios per regression

		Breusch-Pagan	
	CAPM	Three-factor model	Four-factor model
Portfolio	P-value	P-value	P-value
Low Risk	0.634	0.175	0.239
High Risk	0.720	0.088	0.023
Growth	0.012	0.006	0.006
Value	0.000	0.010	0.000
Blend 1	0.011	0.067	0.000
Blend 2	0.009	0.062	0.301
Adjusted Low Risk 1	0.381	0.264	0.237
Adjusted Low Risk 2	0.436	0.200	0.011
Adjusted High Risk 1	0.905	0.021	0.012
Adjusted High Risk 2	0.258	0.043	0.008
Adjusted Growth 1	0.026	0.004	0.006
Adjusted Growth 2	0.005	0.003	0.006
Adjusted Value 1	0.000	0.000	0.000
Adjusted Value 2	0.003	0.231	0.000
Adjusted Blend 1.1	0.001	0.001	0.000
Adjusted Blend 1.2	0.020	0.259	0.002
Adjusted Blend 2.1	0.002	0.601	0.684
Adjusted Blend 2.2	0.000	0.000	0.000

Appendix 5. Durbin-Watson autocorrelation test for the portfolios per regression

	Durbin-Watson		
	CAPM	Three-factor	Four-factor
Portfolio	DW statistics	DW statistics	DW statistics
Low Risk	1.86	1.89	1.87
High Risk	1.92	1.92	1.89
Growth	1.85	1.85	1.86
Value	1.78	1.96	1.91
Blend 1	1.85	1.93	1.89
Blend 2	1.91	1.89	1.90
Adjusted Low Risk 1	1.86	1.87	1.85
Adjusted Low Risk 2	1.83	1.77	1.77
Adjusted High Risk 1	1.93	1.89	1.89
Adjusted High Risk 2	1.89	1.88	1.85
Adjusted Growth 1	1.89	1.89	1.90
Adjusted Growth 2	1.56	1.66	1.65
Adjusted Value 1	1.78	1.92	1.88
Adjusted Value 2	1.79	2.01	1.96
Adjusted Blend 1.1	1.85	1.91	1.88
Adjusted Blend 1.2	1.85	1.95	1.91
Adjusted Blend 2.1	1.91	1.96	1.95
Adjusted Blend 2.2	1.89	1.92	1.91

Appendix 6. Normality test for the residuals of the portfolios per regression

	CAPM		Three-factor model		Four-factor model	
Portfolio	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Low Risk	-0.260	2.057	-0.161	2.316	-0.177	2.405
High Risk	-1.095	13.203	-1.486	13.286	-1.641	14.888
Growth	-0.648	3.248	-0.641	5.549	-0.637	5.589
Value	-0.170	9.223	-0.707	5.951	-1.026	8.604
Blend 1	-0.873	10.966	-0.843	8.828	-1.062	10.279
Blend 2	-0.371	3.467	-0.424	3.048	-0.420	3.233
Adjusted Low Risk 1	-0.283	1.940	-0.137	2.085	-0.146	2.152
Adjusted Low Risk 2	-0.726	5.226	-0.723	5.170	-0.864	6.013
Adjusted High Risk 1	-1.409	15.225	-1.750	16.690	-1.918	18.650
Adjusted High Risk 2	-0.801	10.646	-1.130	9.501	-1.238	10.585
Adjusted Growth 1	-0.570	2.324	-0.547	3.657	-0.555	3.696
Adjusted Growth 2	-1.181	12.026	-1.105	10.251	-1.106	10.270
Adjusted Value 1	-0.292	10.434	-0.869	7.195	-1.309	10.647
Adjusted Value 2	0.037	6.667	-0.397	2.160	-0.593	3.243
Adjusted Blend 1.1	-1.370	15.313	-1.266	13.213	-1.449	14.845
Adjusted Blend 1.2	-0.399	5.755	-0.402	4.836	-0.523	5.375
Adjusted Blend 2.1	-0.211	2.131	-0.310	1.929	-0.294	2.024
Adjusted Blend 2.2	-0.633	5.318	-0.590	5.655	-0.568	5.715

Appendix 7. Multicollinearity test for the explanatory variables

Variable	RMRF	SMB	HML	MOM
RMRF	1.000			
SMB	0.115	1.000		
HML	0.141	0.173	1.000	
MOM	-0.073	-0.219	-0.754	1.000

Appendix 8. Additional results of the CAPM and Fama-French three-factor model

	CAPM		Three-factor model			
Portfolio	RMRF	Adj. R^2	RMRF	SMB	HML	Adj. R^2
Low Risk	2.111***	0.925	2.098***	0.369***	-0.075**	0.932
	(0.018)		(0.018)	(0.036)	(0.024)	
High Risk	2.241***	0.853	2.151***	0.688***	0.481***	0.900
	(0.028)		(0.064)	(0.074)	(0.059)	
Growth	2.246***	0.845	2.283***	0.722***	-0.760***	0.908
	(0.056)		(0.044)	(0.072)	(0.042)	
Value	2.116***	0.814	1.995***	0.221***	1.043***	0.928
	(0.069)		(0.044)	(0.051)	(0.045)	
Blend 1	2.174***	0.881	2.115***	0.432***	0.320***	0.902
	(0.064)		(0.053)	(0.058)	(0.056)	
Blend 2	2.120***	0.925	2.087***	0.455***	0.063**	0.936
	(0.04)		(0.036)	(0.048)	(0.033)	
Adj. Low Risk	2.126***	0.929	2.120***	0.347***	-0.128***	0.936
	(0.018)		(0.017)	(0.035)	(0.023)	
Adj. Low Risk 2	4.420***	0.948	4.344***	0.825***	0.273***	0.959
	(0.032)		(0.028)	(0.057)	(0.039)	
Adj. High Risk 1	2.237***	0.857	2.150***	0.644***	0.477***	0.901
	(0.028)		(0.066)	(0.073)	(0.058)	
Adj. High Risk 2	2.222***	0.866	2.144***	0.646***	0.390***	0.903
	(0.027)		(0.057)	(0.071)	(0.053)	
Adj. Growth 1	2.251***	0.853	2.269***	0.808***	-0.623***	0.905
	(0.049)		(0.039)	(0.061)	(0.041)	
Adj. Growth 2	1.706***	0.287	1.717***	1.282***	-0.824***	0.350
	(0.219)		(0.202)	(0.308)	(0.175)	
Adj. Value 1	2.122***	0.798	1.992***	0.250***	1.108***	0.923
	(0.075)		(0.047)	(0.049)	(0.049)	
Adj. Value 1	2.064***	0.813	1.946***	0.233***	1.002***	0.924
	(0.062)		(0.019)	(0.039)	(0.026)	
Adj. Blend 1.1	2.236***	0.887	2.180***	0.421***	0.299***	0.905
	(0.068)		(0.057)	(0.061)	(0.057)	
Adj. Blend 1.2	2.121***	0.879	2.070***	0.432***	0.246***	0.897
	(0.055)		(0.022)	(0.045)	(0.03)	
Adj. Blend 2.1	2.137***	0.899	2.081***	0.638***	0.186***	0.925
	(0.029)		(0.019)	(0.038)	(0.026)	
Adj. Blend 2.2	2.148***	0.910	2.105***	0.632***	0.068**	0.931
	(0.045)		(0.039)	(0.056)	(0.035)	