Quality Investing in the German Market

Master Thesis

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Abstract

We conduct an extensive literature review into proxies of profitability, growth, safety and ESG that are linked to quality, since quality is missing a univariate definition within factor investing. The factors that positively impact German stock prices are combined into a composite quality score. While the factors profitability, growth and safety have a positive impact on a firm's stock price, surprisingly, the ESG factor does not. We show that quality firms command a higher stock price, even after controlling for additional variables. Based on our definition of quality, we create value-weighted and equal-weighted quality-sorted portfolios for the German market. As the results are inconclusive, we follow the approach of related literature in constructing portfolios conditionally sorted first on size and then on quality. This approach shows significant risk-adjusted returns for both long and long-short investors, predominantly in our small sample. These results are robust for different model specifications. Overall, quality stocks consistently outperform junk stocks in our sample. Quality investing strategies in Germany are profitable with an appropriate definition of quality.

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1 Introduction

Literature on quality investing agrees that investors should be willing to pay a higher price for high-quality companies. No consensus though exists on the question of how quality should be defined. People have different definitions of quality, be it in buying a house or when analyzing a company. However, there are metrics throughout the literature that have been connected to higher quality and further been accepted as such. Among the most common are measures connected to *Profitability* (B. Graham & Dodd, 1934; Haugen & Baker, 1996; Novy-Marx, 2013), *Growth* (Lakonishok, Shleifer, & Vishny, 1994; Mohanram, 2005) and *Safety* (Ang, Hodrick, Xing, & Zhang, 2009; Campbell, Hilscher, & Szilagyi, 2008; George & Hwang, 2010). But what is the ideal proxy for profitability? Does the growth of the profitability proxies provide additional explanatory power? Can the investment into low-risk firms not only be the safe but also the more profitable choice? Our paper aims to answer questions of that kind by deriving our definition of quality.

As we show in this thesis, different authors[1], among them Hsu, Kalesnik, and Kose (2018) and Novy-Marx (2013, 2014a), have argued for different proxies and definitions of quality, and further that combining different proxies increases the performance of the quality score (Asness, Frazzini, & Pedersen, 2018b). As these insights are relatively well examined in prior work for the United States, this paper examines if quality is a factor in the German stock market.

Either quality works universally independent of the market in question, or only in the United States[2]. Asness et al. (2018b) try to answer this question by examining both a US and a global sample in their study[3]. The results from Asness et al. (2018b) suggest that a Quality minus Junk (QMJ) strategy seems to perform well in Germany over a time period from 1995-2016[4], but only limited information on the drivers within the global sample results is given. Using a similar methodology as in Asness et al. (2018b), we want to perform a deep dive into the German market. Germany is globally known to deliver high-quality products such as cars (*Volkswagen, BMW, Mercedes*), sports-ware (*Adidas, Puma*) and software (*SAP*). Does this high-quality aspect translate into a profitable quality investing strategy for the German market as a whole?

[1]Further refer to Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018a); Bouchaud, Stefano, Landier, Simon, and Thesmar (2016); Hanson and Dhanuka (2015); Kyosev, Hanaue, Huij, and Lansdorp (2016) for other work on quality investing

[2]Hsu et al. (2018); Novy-Marx (2013, 2014a) and most others focus their studies on the United States

[3]The authors conclude, that quality investing works in both the US and the global environment

[4]The authors find that their QMJ factor has a Sharpe ratio of 0.61 from 1995-2016 in Germany, outperforming their global sample

The defining difference of traditional quality investing compared to other factor investing strategies such as Value or Momentum investing is that it uses accounting data rather than historical stock performance as the base for investing. This allows investors to build up a strategy solely by looking at companies' annual reports[5].
Recently, another factor based on publicly available data and not related to historical stock returns has been related to high quality. This factor is based on a firm's Environmental, Social and Corporate Governance performance, combined to an *ESG* score[6]. Including an *ESG* score as a quality factor would make sense if investors are willing to pay a higher price for firms with a higher *ESG* score.

The focuses detailed above are incorporated into the research question of our thesis:

Which factors and characteristics determine the quality of a company, and can investing based on that quality definition produce significant excess returns where Quality outperforms Junk?

In answering our research question, we want to assess how influential quality investing studies define quality, which quality characteristics they use, and based on those, define our own quality score.

Still, why would the investor care for quality if there is no link to a profitable strategy?
Using the dividend discount model, we derive a stock price definition which Asness et al. (2018b) related to the three quality components *Profitability, Growth* and *Safety.* These three factors are shown to positively affect a firm's Market-to-Book Equity ratio.
Regressing the Market-to-Book ratio on *Profitability, Growth* & *Safety*, we find that the factors command a higher stock price.
In addition to the quality factors used in Asness et al. (2018b), we add an ESG score to our model. As not all firms have ESG scores within our sample, we analyze a subsample only including ESG score firms for quality. Interestingly, the ESG score has a negative effect on the Market-to-Book ratio, implying that a higher ESG score entails a lower stock price.

Sorting our full sample by our definition of quality into five market value-weighted and equally-weighted portfolios, we create long and long-short investing strategies. Following related quality investing strategy work such as Asness et al. (2018b), Kozlov and Petajisto (2013) and Novy-

[5]Refer to Hsu et al. (2018) and Novy-Marx (2014a) for a more detailed explanation.
[6]Authors have argued for the quality of *Environmental* (Flammer, 2013), *Social* (Edmans, 2011) and *Corporate Governance* (Gompers, Ishii, & Metrick, 2003), and for the benefits of including a non-financial measure such as ESG into a quality score (Melas, Nagy, & Kulkarni, 2017)

Marx (2014a), we adapt our approach to first sort our sample by size and afterward for quality. This creates value-weighted quality and junk portfolios for both small and big companies. Overall, the high-quality portfolios outperform the low-quality portfolios, using different model specifications. Our long-short strategies perform similarly well, especially when used on our small size sample.

After this introduction, the structure of this paper is as follows: Section 2 discusses related literature on quality investing and, crucially, examines proxies for the factors *Profitability, Growth, Safety* and *ESG*. In Section 3 we establish the theoretical framework for cross-sectional quality regressions and for assessing the performance of investing strategies. Section 4 explains the data sources as well as the clean-up procedure to prepare the data for our analysis. Section 5 gives the intuition behind the construction of the quality factors and the investing strategies. Section 6 shows the results of our quality regressions and investing strategies, while section 7 discusses our thesis' approach. Section 8 concludes.

2 Literature Review

The environment of factor investing is not uncharted territory. Even before the influential factor investing models of Fama and French (1993, 2015) in which the authors developed first the three-factor investment model and later as an extension the five-factor investment model, there have been studies investigating the relation between stock returns and the investment focused on specific firm characteristics.
The earliest of which probably stems from Ross (1976), who laid the groundwork for explaining returns with a combination of different firm factors playing together. However, even though many authors have addressed the concept of factor investing, the various factors have not necessarily received equal attention in research. While factors such as value investing, developed based on work by B. Graham and Dodd (1934), (extended by Fama and French (1993), Buffett (1984), Lakonishok et al. (1994) among others), momentum strategies (Jegadeesh and Titman (1993), Fama and French (1993), Asness, Frazzini, Israel, and Moskowitz (2014) among others) or size related strategies (Banz (1981), Fama and French (1993), Asness et al. (2018a) among others) have been investigated by many authors, the factor investing based on a firm´s quality metrics has not received as much attention.

A reason for the lack of research into quality investing is the missing univariate definition for quality. Many studies mentioned below relate a firm's quality metrics to stock returns or form portfolio strategies based on quality measures, but researchers either disagree on what constitutes quality, or their work focuses on a limited set of factors associated with quality.

These proxies for quality are often considered separately, without combining them into a composite score[7].

One of the first but certainly the most influential study to deliver such a definitive score of a company's quality was done by Asness et al. (2018b). The authors there create a quality score based on several metrics within the characteristics *Profitability, Growth* and *Safety* that the authors associate with quality. Asness et al. (2018b) argue that investors should be willing to pay a premium for higher quality in these characteristics and find that firms exhibiting better quality characteristics on average have higher stock prices. Based on the quality score they define, a factor portfolio called Quality-minus-Junk (QMJ) is created, similar in its long-short characteristics to the factor portfolios of Fama and French (1993, 2015), that buys stocks with a high-quality score and shorts stocks with a low-quality score. Next, the authors regress the QMJ portfolio returns on the market, size, value, and momentum factors from Fama and French (1993) and Carhart (1997), to check if their returns are explained by these factor exposures.
Their QMJ portfolio delivers significant abnormal returns. As an explanation for the performance of the QMJ portfolio, either a risk-based anomaly, that quality stocks underperform in distress, or a mispricing anomaly, that markets are inefficient and underprice quality, are presented. The authors show evidence for an average underpricing of high-quality of 10,72% and an equal average overpricing of low-quality, arguing that the mispricing of quality stems from market inefficiency. Further, high-quality stocks are found to be less risky compared to low-quality stocks, finding overall no evidence for the risk-based anomaly explanation.
The authors are examining two different samples. Their main sample focuses on the US and a second sample on the global market. The global sample includes the German market, making it the only quality investing paper of our knowledge to do so.

Bouchaud et al. (2016) investigate why quality investing is able to provide significant alphas and sharpe ratios, even though all cash flow related information (here used as a proxy for profitability) is public information. Two possible explanations are given: Either those excess returns stem from a risk premium for quality firms, which contradicts previous research but would be in line with the Efficient Market Hypothesis. Or otherwise, investors and stock markets continuously undervalue high quality.
The results support the previously mentioned literature. Even after accounting for risk, the returns of quality stocks are abnormally high. The authors find evidence for their second hypothesis, which they call the "Behavioral view". Analysts underestimate future returns of high quality because they pay little attention to profitability measures while focusing too much on earnings. These results imply that analysts under-react to news about firms, which is in line

[7]Refer to Hsu et al. (2018), Novy-Marx (2014a) among others.

with the inefficient market hypothesis that Asness et al. (2018b) found as a reason for mispricing.

Similarly to Asness et al. (2018b), Kyosev et al. (2016) also use a model that ranks firms after their performance within certain quality characteristics. The authors test a variety of quality factors used in previous literature for their ability to predict stock returns because, in their opinion, no univariate measure of quality exists. They show that only the quality factors that forecast earnings growth predict stock returns. Next, five equally-weighted portfolios are constructed that rank the firms with so-called z-scores[8] based on the quality factors that have the power to predict stock returns. An investment strategy that goes long the portfolio with the highest quintile of z-scores and short sells the portfolio in the lowest z-scores quintile is constructed, similar to the QMJ factor created by Asness et al. (2018b). This *Top-minus-Bottom (T-B)* strategy outperforms the single-factor strategies and earns an annual alpha of 6%. These results show that quality strategies focused on earnings can deliver significant excess returns, which encourages the inclusion of earnings growth factors in a quality score, but inadvertently agree with the conclusion of Bouchaud et al. (2016) discussed above. Earnings get too much attention by analysts, so possibly the *T-B* strategy should deliver even higher returns.

An approach focused on comparing quality investing to other factor investing strategies has been conducted by Novy-Marx (2013, 2014a) to assess which common quality strategies work best. The author emphasizes the many similarities between quality and value strategies, stating that quality can be seen as a value strategy with a different implementation. Novy-Marx (2014a) further argues that both can serve as complementary strategies, as one strategy performs well when the other has large drawdowns. The difference between both strategies being that value strategies buy normal assets at discounts, while quality strategies buy highly productive assets. Novy-Marx (2013) specifies that value strategies aim at buying cheap assets through the sale of expensive assets, while quality strategies buy productive assets financed by the sale of unproductive assets.
This relation is also argued for by Frazzini, Kabiller, and Pedersen (2018), who show that the performance of Berkshire Hathaway, the investment company led by famous quality investor Warren Buffet, stems from investments in cheap, high-quality firms.
It is also argued that strategies combining quality and value elements can achieve higher returns than one strategy alone. A corresponding strategy is put forward by Asness et al. (2018b), who construct a *quality at a reasonable price* strategy that buys cheap securities relative to their quality and achieves a higher Sharpe ratio than sole value or quality strategies.

[8]Z-scores are used my a multitude of authors to assess quality characteristics, but these scores are not necessarily the same.

While the literature discussed above is among the most important in quality investing, we want to investigate whether the ESG factor can also be considered a quality factor in this thesis. The studies below are some of the few that include an ESG factor in their quality investing papers.

Hanson and Dhanuka (2015) performed an analysis that combines quality strategies based on traditional financial signals with ESG-related metrics. As our paper aims to achieve a similar combination, the results of the work by Hanson and Dhanuka (2015) could be of great relevance. The authors argue for an extension of classical quantitative quality strategies with an additional qualitative part. They argue further that ESG data has a forward-looking dimension because it reflects in part a future commitment. In contrast, financial data deals with assessing past performances. Their approach to regress various ESG scores on market performance finds mixed results. Even though the authors' corporate governance scores have a high positive impact on market performance, both the environmental and social scores have negative coefficients, albeit not consistently significant. The authors conclude from this finding that corporate governance is the essential non-financial proxy for quality. Overall, Hanson and Dhanuka (2015) emphasize the importance of combining quantitative with qualitative quality factors.

A different type of study that focuses on comparing performances of previous research was performed by Hsu et al. (2018), who analyze factors in related literature associated with quality, assess their robustness in multiple model specifications by deriving the quality factor premium, and lastly compare the returns of the strategy across different geographical areas. While their analysis includes significantly fewer quality factors, it again sheds light on the area left untouched in Asness et al. (2018b), the *ESG* score. Hsu et al. (2018) argue that the robust measures in their model can be related to ESG performance. Specifically, the authors relate high profitability and a conservative investment level to good governance because that combination denies managerial empire building and damaging levels of risk-taking due to misleading management incentives. They further argue for a good social performance linked to their quality factor of high accounting quality due to ensured compliance and integrity. Overall their strategy to directly incorporate ESG metrics into a quality score has interesting properties for us, as it uses a similar methodology in normalizing quality measures, including *ESG*, to be able to define a combined quality score.

Due to the features of the paper by Asness et al. (2018b) of not only defining a quantifiable score for quality but also creating a portfolio strategy that invests based on this quality definition, our work will build on a similar methodology as the work of Asness et al. (2018b).

We begin our approach by evaluating their definition of quality by diving into the various proxies used within the factors of *profitability, growth* and *security*. Similarly to Hsu et al. (2018), we will separately examine the use of these factor proxies in the relevant literature to assess whether the proxies are linked to quality in prior studies and should therefore be included in a composite quality factor. In addition to Asness et al. (2018b)'s quality factors *profitability, growth* and *safety*, we also present literature relating an ESG score to quality characteristics.

2.1 Profitability

One of the most important factors linked to quality is a company's profitability. Haugen and Baker (1996) find that higher profitability is linked to higher than average stock returns and further is less risky than less profitable stocks. From a hedging point of view, Novy-Marx (2014b) find value and volatility factors to be negatively correlated with profitability, which they use to argue that investing based on profitability serves well as a risk-adjusting strategy for value and volatility loaded portfolios.
As Asness et al. (2018b) does not explain his motivation behind the inclusion of their profitability proxies, this section will investigate why other authors have used these proxies to assess if these measures are valid profitability proxies.

2.1.1 Return on Equity

Return on equity (ROE) is one of the most common proxies for profitability, as it links a firm's operating performance directly to the return that the firm's shareholders receive.
It is very prominently used by Fama and French (2015) in their extension of Fama and French (1993) as an additional factor in their five-factor asset pricing model as a profitability measure. Fama and French (2015) find its significance in predicting average returns and argue that its inclusion renders the value factor of Fama and French (1993) insignificant.
Haugen and Baker (1996) use ROE amongst other sets of measures for profitability and find that those are accurately forecasting stock returns.
Frankel and Lee (1998) regress a firm's valuation on future Return on Equity and find that this method can predict long-term stock returns.
Further Hou, Xue, and Zhang (2012) propose a new four-factor model including ROE as a proxy for profitability to predict portfolio returns. The authors assess that higher ROE firms will earn higher returns than low ROE firms. Further, higher ROE firms are more profitable and therefore less financially distressed, which should lead to higher average returns compared to firms in financial distress. As ROE has been used extensively in previous research, including studies within a quality investment framework, its inclusion as a profitability measure in this paper is a logical consequence.

2.1.2 Return on Assets

While we have already decided to include ROE, also using Return on Assets (ROA) as a proxy for profitability makes sense from the firm's financing perspective. In contrast to ROE, ROA gives the return on the whole company's financing, regardless if the enterprise is financed by debt or equity.

Mohanram (2005) uses ROA as a proxy for profitability to analyze low Book-to-Market firms, which are typically quality firms. He argues that firms with a high ROA are likely to also be profitable in the future, therefore creating a direct link between ROA and possible quality firms. The author further includes a measure of ROA, where he replaces Net Income with Cash Flow in the numerator as a profitability measure. This implies that both Net Income-ROA and Cash Flows-ROA complement each other as profitability proxies. He includes both factors, among others, to create an investing strategy based on the performance of low Book-to-Market firms. He concludes that this strategy works well with quality firms and not as well with value firms. Bouchaud et al. (2016) further finds that investors focus too much on earnings per share while overlooking profitability items such as ROA or ROE. Overall, ROA shows similar properties as ROE for a proxy of profitability, but we include it nonetheless for the reasons discussed above.

2.1.3 Cash Flow over Assets

As pointed out above in the investigation into ROA, Net Income and Cash Flow work well as complements for profitability. In order to normalize the cash flows to compare them between companies, Cash Flows are divided by total assets (CFOA), similarly to the other profitability measures.

Sloan (1996) argue that stock prices often fail to reflect the cash flow components of future earnings because investors rely too much on reported earnings in their future earnings prediction. Sloan (1996) concludes that cash flows could be better equipped for measuring profitability, as they paint a broader picture of future earnings for a company.

Cohen, Gompers, and Vuolteenaho (2002) find that in response to positive cash flow news, institutions overload on the stocks of the respective companies to take advantage of the subsequent high returns. This supports Sloan (1996) 's study in a sense that those institutional investors expect the positive cash flow news to transform into a higher company profitability. The connection between high profitability and outperforming stock returns based on the Dividend Discount Model has been shown by many authors (e.g. Cohen et al. (2002); Novy-Marx (2013, 2014a)). We include CFOA to ensure that the income stems from ordinary business activities and does not consist primarily of one-off items.

2.1.4 Gross Profitability over Assets

Novy-Marx (2013) predominantly uses Gross Profitability over Assets (GPOA) as his quality measure and finds that it has the same power to predict average returns as the book-to-market ratio. It would therefore show the direct link to the valuation of the company. A higher GPOA is linked to significantly higher returns, despite already higher valuation ratios. The author argues for GPOA as the preferred measure of profitability, as it is seemingly not affected by accrual estimates or non-cash items such as depreciation. Further, GPOA has the same predictive power in regards to expected returns as the Book-to-Market ratio and predicts expected returns significantly better than Net Income. This insight is confirmed by Ball, Gerakos, Linnainmaa, and Nikolaev (2015), who explain this finding with the book equity that deflates Net Income, while gross profitability is deflated with book assets. In addition, gross profitability strategies can serve as a hedge to value investors, as those strategies are highly negatively correlated with value strategies (Novy-Marx, 2013).
In subsequent work, Novy-Marx (2014a) compares his previous work[9] with quality strategies based on other measures such as Graham's quality and earnings quality and finds the superior performance of gross profitability. A similar measure is used by Fama and French (2015), who use operating profitability as their quality measure and show that this strategy generates similar high stock returns as in Novy-Marx (2013). As GPOA is closely aligned with not only profitability but has further directly been used as the main focus of a quality investment strategy, we will include it as a proxy for profitability.

2.1.5 Gross Margin

Gross Margin (GMAR) is used by Asness et al. (2018b) as an additional proxy for profitability. Further, Piotroski (2000) uses GMAR in a composite score of financial performance signals. GMAR is found to show significance in explaining the stock returns of the author's analysis. The relationship between stock returns and gross margins is disputed by Novy-Marx (2013), who finds that it does not show statistical significance for explaining excess returns. He further shows, that GMAR provides limited added value when combined with other profitability matters such as gross profitability. As the literature is further limited on the inclusion of GMAR as a profitability proxy, we will not include it in the profitability factor.

2.1.6 Low Accruals

To understand the intuition in including low accruals as a profitability factor, one must consider the relationship between accruals and net income. Managers may have an incentive to aggressively use accruals in order to inflate accounting income, as markets often use accounting

[9]Refer to Novy-Marx (2013) for the details

income to determine management performance (Chan, Chan, Jegadeesh, & Lakonishok, 2006). Therefore high use of accruals is linked to "Low Earnings Quality". Chan et al. (2006) further find a high negative correlation between accruals, measured as the difference between accounting earnings and cash flows, and subsequent stock returns. If firms further have high earnings relative to cash flows, they again have low earnings quality because management inflates these earnings beyond the level of cash flows. Those firms are found to have low future stock returns and underperform compared to firms with low accruals use (Sloan, 1996). Based on his findings, Sloan (1996) creates a portfolio that goes long the decile of firms with the lowest accruals and shorts the decile of firms with the highest accruals. The portfolio earns an average annual return of 10%.

Xie (2001) confirms the results of Sloan (1996) but finds that the accrual overpricing stems mainly from abnormal accruals. Further work on the relationship between accruals and cash flows has been performed by Rayburn (1986), who agree on the connection of cash flows and accruals with returns.

Overall the literature shows that limited use of accruals is correlated with higher quality and sustainability of earnings. Higher earnings then stem from high profitability and not from the use of accounting tricks. The inclusion as a profitability proxy could distinguish the companies that are actually profitable from those who pretend to be.

2.2 Growth

The second factor, for which we will examine prior work related to quality investing, is *Growth*. The factor is used less in the relevant literature, therefore we will not describe each proxy included by Asness et al. (2018b) separately, but instead, we will combine the existing literature in this section.

It is fair to say that the growth measures are closely tied to the profitability measures we have decided to include. However, the intuition behind including them is nonetheless interesting. Asness et al. (2018b) use growth as a factor in their quality score, as they argue that investors should be willing to pay higher prices for growth of profits. The relation of sustainable profits to book values should further be examined over a five-year period because this eliminates the "noisy" part of profits. Their analysis finds indeed that higher growth is connected to higher quality and should therefore command a higher price.

An important work in linking growth in profitability items to quality was put forward by Mohanram (2005). There the use of financial statement analysis to develop an investing strategy for low Book-to-Market ratio firms is investigated. The applicability of financial statement analysis is argued for with the limited usefulness of traditional fundamentals in growth stocks. The authors further create a score based on the growth fundamentals and find that a portfolio going long stocks with good growth fundamentals (high score) and short a portfolio with low

growth fundamentals (low score) earns significant abnormal returns, even though mainly from the short position. Lastly, the same analysis is performed for high Book-to-Market firms to check for robustness. The long-short strategy does not work for high Book-to-Market firms (Value stocks), indicating that growth is specifically a factor for quality firms.
Lakonishok et al. (1994) use past growth in revenue, earnings and cash flows as a measure of performance. Using these past performance measures, the authors find that differences in expected future growth between different factor investing strategies are linked to past growth. The authors explain their findings with a constant overestimation of future growth rates for glamour stocks[10] compared to value or quality stocks. This result confirms that if stocks have constant high growth rates, it can be linked to high quality.

Other work not directly related to quality investing strategies provides further inside into the value of growth rates. Piotroski (2000) uses the 1-year change in ROA in his *F-score*, which uses financial statement analysis on high Book-to-Market ratio firms. Even though a strategy based on his combined score achieves significant abnormal returns, the individual signal of 1-year changes in ROA is not significant. This result might stem from focusing on high Book-to-Market firms while we examine the opposite. Penman and Zhang (2002) link future growth in profitability to conservative accounting, which aligns with the observed connection between low levels of accruals and profitability discussed above. While the literature on the relationship between growth rates and quality is somewhat limited, as mentioned at the beginning of this section, high growth is nonetheless connected to high quality.

As discussed above, the growth measures are linked to the profitability proxies discussed in section 2.1. As we define the profitability proxies similar to Asness et al. (2018b), we will further include the same growth definitions to stay consistent in our approach. The growth measures included are growth in ROE, growth in ROA, growth in GPOA and growth in CFOA, as further explained in section 5.1.2. Since we do not include gross margins as a proxy for profitability, we will also not include the growth of gross margins.

2.3 Safety

The third factor for which we dive into the related literature is safety. Hereby two effects have to be differentiated: First, safety can be understood in connection to risk, so that it measures the probability of going into financial distress or even bankruptcy. Second is the safety of having stable returns, so no suddenly plummeting stock price. We will examine measures connected to both types of safety in the following section.

[10] Glamour stocks are highly demand because they have performed well in the past and have high Price/Earnings ratios

2.3.1 Earnings Volatility

Earnings volatility is the first factor related to the safety of the company. In a similar matter as discussed in 2.1.5 with the low accruals, highly volatile earnings also indicate that cash flows and earnings are very different in magnitude. The company's earnings then come from accounting measures rather than from performance due to good fundamentals (Chan et al., 2006). Asness et al. (2018b) include earnings volatility in their safety score, where they consider lower earnings volatility as safer. This assessment is confirmed by Novy-Marx (2014b), who relates high earnings volatility to low quality.

That more volatile earnings are considered riskier compared to smoother earnings further implies that companies with volatile earnings have to pay a higher risk premium and therefore have higher costs of debt and equity. This is why most CFOs prefer smooth earnings (J. R. Graham, Harvey, & Rajgopal, 2005).

Dichev and Tang (2009) argue that earnings volatility stems from two different sources, first economic shock volatility and second, volatility from accounting determination of income. They further find that low earnings volatility is very persistent, while high earnings volatility is quickly mean-reverting and shows low predictability for future earnings. Additionally, highly volatile earnings are caused by extreme earning events.

Earnings volatility tends to be higher for younger firms and for firms with more volatile profitability (Pástor & Veronesi, 2003). A similar argument for the inclusion of earnings volatility can therefore be made for the inclusion of profitability volatility because firms with sustained profitability also have a lower probability of financial distress (Hou et al., 2012). We include Asness et al. (2018b) 's definition of earnings volatility in order to be able to explain the relation between volatility in earnings and financial distress.

2.3.2 Leverage

The most intuitive factor that influences the risk of financial distress or even bankruptcy is leverage. While Asness et al. (2018b) does not explain their inclusion of leverage as a safety proxy, we will examine related literature that links leverage to safety below.

Starting with the groundbreaking work of Modigliani and Miller (1958), the relationship between a firm's choice of capital structure and the effect on its returns has been investigated. Under the framework of Modigliani and Miller (1958), increasing leverage adds financial risk to the company and should therefore be rewarded with higher returns. The positive relationship between leverage and returns is agreed with by Bhandari (1988), who finds a positive correlation between the debt/equity ratio and future stock returns. Bhandari (1988) concludes that higher leverage carries a premium, which is in excess of a risk premium.

To examine if leverage can be used as a safety proxy, a two-folded investigation has to take place. First, the relationship between leverage and returns has to be explained. And second, how is leverage linked to financial distress. George and Hwang (2010) find that leverage and risk-adjusted returns are highly negatively related. They assess that low leverage and low financial distress levels carry a return premium. George and Hwang (2010) further find that leverage levels are negatively correlated with the costs that a company faces in distress. Firms with high distress costs should optimally be levered up less than firms with low distress costs. The concept of financial distress is also investigated by Campbell et al. (2008), who aim to quantify financial distress to measure returns of stocks in distress, implying a high bankruptcy probability. The main finding of their study is that stocks with high bankruptcy or failure risk deliver low average returns. When creating portfolios sorted by levels of bankruptcy risk, the portfolios with the highest distress levels have low returns, high volatility and high market betas.

Garlappi, Shu, and Yan (2008) agree with the results of Campbell et al. (2008), but add that returns are decreasing in the amount of power shareholders have to extract benefits from the company. This shareholder recovery effect leads to a "hump-shaped" relationship between returns and bankruptcy risk for a firm in financial distress (Garlappi & Yan, 2011). Lastly, low leverage is linked to higher safety and lower levels of financial distress (Norges Bank, 2015).

Overall we can conclude that the related literature disagrees with the idea of a market premium for financial distress, but that rather a premium for low leverage firms exists due to their safety features. Further, higher leverage implies a higher probability of financial distress. These insights lead us to include leverage as a measure of a company's quality, with low leverage being associated with higher quality.

2.3.3 Z-Score

In addition to the levels of leverage that impact a firm's probability of financial distress, several scores that combine different firm-specific financial metrics to directly measure bankruptcy risk have been constructed. As bankruptcy risk can serve as an ideal proxy for financial distress (Altman, 1993), these scores are connected to a firm's safety.

One of these scores is the *Z-score* defined by Altman (1968), where the author combines an analysis of companies' financial ratios with an empirical framework to assess the bankruptcy risk of a company. Altman (1968) builds on the bankruptcy prediction study by Beaver (1966), where accounting data five years before bankruptcy is compared to the same data of non-bankruptcy firms, and argued that bankruptcy can be predicted. Altman (1968) uses similar accounting data in a multiple-discriminant analysis and finds his model to be highly precise in predicting a firm's bankruptcy, with a 94% success rate in his initial sample. Even though the initial analysis of Altman (1968) is performed with sample data from 1946 to 1964, a later study by Begley, Ming, and Watts (1996) has failed to improve the model's performance with more recent data. This implies, that the *Z-score's* relevance for bankruptcy prediction holds

independent of the sample period.
The *Z-score* as a measure of bankruptcy risk is related to portfolio returns in Dichev (1998), who finds an inverted U-shape between Z-scores and portfolio returns. Portfolios with the lowest and highest *Z-score* achieve lower than average returns. Dichev (1998) also finds that firms with low bankruptcy risk (high *Z-score*) show variations in the *Z-score* not explainable by bankruptcy risk volatility, implying that the *Z-score* captures additional firm characteristics for these companies as well.
It seems overall safe to say that Altman (1968) *Z-score* is not only a useful quantification of a firm's bankruptcy risk but additionally has not lost its relevance in other sampling periods. By including the *Z-score* as a safety measure in our quality score, we include a proven bankruptcy risk measure.

2.3.4 O-Score

Similarly to the *Z-score* discussed above, the *O-score* is also a measurement for bankruptcy risk. It was developed in Ohlson (1980) and extends Altman (1968) and other studies that aim to predict bankruptcy such as Beaver (1966), Deakin (1972), Blum (1974) and Edminster (1972) among others. The *O-score* uses a more recent time period from 1970-1976 and a broader data set that includes more companies as in Altman (1968). In contrast to most of the previous work, Ohlson (1980) uses 10-K financial statements data to make use of the public availability of these statements. Ohlson (1980) sees the advantage of this approach in the fact that by checking the statement release dates, one can see whether bankruptcy occurred before or after the statement's release. When comparing the *O-score* and the *Z-score*, one has to pay attention. While a high *Z-score* implies a low probability of bankruptcy, a high *O-score* aligns with a high probability of bankruptcy. Hence, both scores are negatively correlated (Dichev, 1998).
Dichev (1998) uses both scores in his study of bankruptcy risk because the models complement each other due to differences in time periods, data samples, and methodologies, as discussed above. Zmijewski (1984) adds his own score for bankruptcy and confirms that both *Z-score* and *O-score* provide explanatory power and are at least somewhat complementing. As discussed above for the *Z-score*, the *O-score* has similarly been tested with data from different time periods and proven to still be relevant (Begley et al., 1996).
Nonetheless, some more recent studies have doubted the accuracy of using only accounting data for bankruptcy prediction because of their perceived limited information content. Hillegeist, Keating, Cram, and Lundstedt (2004) compare the information properties and performance in bankruptcy prediction of the *O-score* and *Z-score* with a bankruptcy predictor based on a Black-Scholes-Merton (BSM) option pricing model, an approach that is also used in Vassalou and Xing (2004). Hillegeist et al. (2004) argue that their approach adds significantly more information compared to the *O-score* and *Z-score*. A main advantage of the BSM bankruptcy

predictor is the flexibility across international accounting regimes. As we only focus on the German market, this apparent advantage is irrelevant to us.
We conclude that it is sufficient to use *O-score* and *Z-score* as measures of bankruptcy risk and refrain from additionally including the approach developed by Hillegeist et al. (2004). These bankruptcy risk scores help to include a broader company safety view into our quality factor, as they combine different measurements that can be perceived as safety proxies. This makes our quality score less vulnerable to outliers, which is why we similarly to Asness et al. (2018b) include both scores.

2.3.5 Low Beta

Asness et al. (2018b) associates with safety is a low beta. The beta factor builds on the idea that safety comes from having low exposure to the market portfolio. High beta assets are said to be riskier and to come with low risk-adjusted returns (Black, Jensen, & Scholes, 1972). Contrary to the predictions of the CAPM model, Frazzini and Pedersen (2014) finds that the Security Market Line[11] is too flat in reality, which leads to low beta stocks having higher expected returns than predicted.
But Novy-Marx (2014b) has a different view on the use of low beta as a measure for safety. He argues that low beta is not a quality measure but is based on a data mining approach focused on short-term market factors. One should rather base quality metrics on long-term business fundamentals. Further, Novy-Marx (2014b) shows that factor investing strategies based on low betas, called "defensive" stocks, tend to be tilted towards high profitability stocks. This implies, that the actual quality aspect is profitability, not the safety within low beta.
Finally, the unique feature of quality investing strategies is that it is possible to develop a strategy independent of historical stock performance based only on publicly available accounting data. However, the calculation of the beta factor would require the use of historical stock and market prices, which would contradict the generally accepted understanding of quality investing (Hsu et al., 2018). We decide against including the low beta factor as a safety measure for the reasons outlined above.

2.4 ESG

In the recent past, factors related to a company's Environmental, Social and Corporate Governance (ESG) performance have been associated with quality. After discussing previous quality investing strategies that include an ESG factor above, we will in this section explain the intuition behind the three subfactors of ESG and how those are related to a firm's quality. Different papers have demonstrated the connection between the firm's ecological performance and its val-

[11] The Security Market Line is further explained in section 3

uation. Cormier and Magnan (1997) find an inverse relationship between a firm's pollution and the stock market valuation, which they explain with the environmental liabilities that those companies have.
Several authors, among them Klaasen and McLaughlin (1996) and Flammer (2013), have shown a connection between environmental performance and stock price reaction, particularly that good environmental news trigger positive stock price reactions. In contrast, negative environmental news can trigger a firm's stock price to go down. Flammer (2013) finds an average positive alpha of 0.84% as a result of positive events and a negative average alpha of -0.65% as a reaction to negative news.
Eccles, Ioannou, and Serafeim (2014) have further shown a connection between a high overall sustainability score and higher stock returns for a company, which indicates a positive alpha for investing in sustainability. The authors create portfolios based on a sustainability index and find that the portfolio with high sustainability scores outperforms the low sustainability portfolio by 4.8% annually. The better stock performance also holds when comparing highly sustainable companies to peers without a specific ESG focus (Statman & Glushkov, 2009). As the sustainability score is an ESG score focused solely on the ecological aspect, these results are encouraging for us as they show that high ecological quality can deliver high returns.

Similar connections can be found between a company's social performance and its stock market valuation. In a study focused on employee satisfaction, Edmans (2011) finds that constructing a portfolio going long in the 100 companies with the highest employee satisfaction rate earns an annual alpha of 3.5%. He argues that employee satisfaction is not priced accurately by the stock market. Further work into employee satisfaction comes to similar results (Faleye & Trahan, 2011; Fulmer, Gerhart, & Scott, 2003).
Other studies also find support for the idea that better social performance can increase stock prices, for example, with respect to higher philanthropic expenses (Brammer & Millington, 2008; Godfrey, 2005).
Lastly, there is a class of papers that aim to classify a company's corporate governance as a factor associated with quality, implying that good corporate governance leads to an increased company quality score. A very influential work on governance was performed by Gompers et al. (2003). The authors create an index capturing provisions for shareholder rights, called Governance index (*G-index*). Using the *G-index*, an investment strategy that buys firms with the strongest shareholder rights ("Democracy firms") and shorts firms with the weakest shareholder rights ("Dictatorship firms") achieves annual returns of 8.5 %. The authors further link strong shareholder rights to high firm value, high profits, high sales growth, low capital expenditure and fewer acquisitions. Based on the provisions outlined by Gompers et al. (2003), Bebchuk, Cohen, and Ferrell (2009) create an entrenchment index including six different shareholder

rights focused on anti-takeover amendments. The results confirm Gompers et al. (2003) assessment that weak shareholder rights are correlated with a decrease in firm value and significant negative abnormal returns, even though Bebchuk et al. (2009) find no correlation between the other 18 provisions with a firms valuation. However, this correlation outlined by Bebchuk et al. (2009) disappears after 2000.

For companies with weak shareholder rights, Core, Guay, and Rusticus (2006) find that the performance inefficiencies do not surprise the stock markets but rather are already priced in. Therefore the firm's valuation is lower than in an efficient state, leading to no impact on the stock returns.
The link between governance, company valuation and profitability is further disputed by Johnson, Moorman, and Sorescu (2009). They re-examine the hedge portfolio proposed by Gompers et al. (2003) and the adaption of Bebchuk et al. (2009) and find no abnormal returns on a long-term basis. The authors imply from their results that the governance quality has no impact on abnormal stock returns but that the results of Gompers et al. (2003) and Bebchuk et al. (2009) are instead asset pricing misspecifications or stem from unexpected industry performance. As a possible explanation for the differing results, Johnson et al. (2009) point out a distributional anomaly of "Democracy" or "Dictatorship" firms, mainly that the portfolios show industry clustering. Johnson et al. (2009) is supported by Lyon, Barber, and Tsai (1999), who show that tests of long-term abnormal returns are error-prone, especially in the presence of industry clusters.

The topic of industry heterogeneity is also investigated by Giroud and Mueller (2011), who draw a distinction between corporate governance in competitive industries and corporate governance in non-competitive industries. The authors confirm the results of Gompers et al. (2003) and Bebchuk et al. (2009) that bad corporate governance is correlated with low stock returns, low firm value and slack in profitability, but only for firms in non-competitive industries. According to Giroud and Mueller (2011), the inefficiencies stem from high production costs and low working productivity within non-competitive firms.
The missing correlation between governance and efficiency for firms in competitive industries is reasoned with the competitive pressure that disciplines managers to maximize performance, creating less need for good corporate governance. Company performance is thereby ensured through competitive profitability targets (Hart, 1983).

An approach that focuses more specifically on internal and external governance factors was performed by Cremers and Nair (2005) to avoid including upper management turnover in their corporate governance classification. Among others, assessing corporate governance by management turnover creates a selection bias (Huson, Malatesta, & Parrino, 2004). Cremers and Nair (2005) define internal governance as shareholder rights and external governance as a company's takeover vulnerability and find that both complementary are related to long-term abnormal returns. Further, the authors find that a strategy going long in high takeover vulnerability and short in low takeover vulnerability firms creates returns between 10% and 15%, but only if the share of active shareholders is high.

Overall, we can conclude that a company's performance with regard to ecological, social and corporate governance factors can positively impact a company's stock price. In order to capture this performance, we will include a combined ESG score as it is widely accepted as a measure of interest.

3 Theory

In the prior section, we have examined the factors related in the literature to high quality and have decided which proxies we use in the computation of our quality score. Next, we will provide the theoretical framework necessary to show that investors are willing to pay a higher price for quality. We start by deriving the Market-to-Book ratio.

3.1 Dividend Discount Model

The Market-to-Book ratio is derived similarly as in Fama and French (2006), Novy-Marx (2013) and Asness et al. (2018b).
If an investor is willing to pay a higher price for quality, it implies that the firm's higher valuation is due to good quality (Asness et al., 2018b). As Fama and French (2006) show, in the dividend discount model, the market value of a firm equals the present value of expected future dividends.

$$M_t = \sum_{t=1}^{\infty} \frac{E_t(D_{t+1})}{(1+r)^t} \tag{1}$$

where M_t is the market value of the firm at time t, $E_t(D_{t+1})$ is the expected dividend of the firm at time *t+1* and r is the required rate of return on the expected dividends. Using clean surplus accounting, the change in the firms book equity equals the firms retained earnings. Equation 2 links earnings to dividends and the firm's book value and is shown below.

$$B_t = B_{t-1} + Y_t - D_t \tag{2}$$

where Y_t are the equity earnings of the firm. By solving the clean surplus accounting expression above for the dividends in time t and by defining the change in book equity as $dB_t = B_t - B_{t-1}$, we get to the following expression that shows the market value of equity.

$$M_t = \sum_{t=1}^{\infty} \frac{E_t[Y_{t+1} - dB_{t+1}]}{(1+r)^t} \tag{3}$$

Equation 3 has implicitly defined the dividends as the earnings of the firm minus the change in book equity. By dividing both sides of the equation by the firm's book value of equity, we get the ratio of the firm's market value to its book value:

$$\frac{M_t}{B_t} = \frac{\sum_{t=1}^{\infty} \frac{E_t[Y_{t+1} - dB_{t+1}]}{(1+r)^t}}{B_t} \tag{4}$$

Equation 4 can also be written in terms of residual income, by defining residual income as $RI_t = Y_t - dB_{t-1}$. The Residual income can be understood as the part of earnings Y_t in excess of the cost of book equity (Asness et al., 2018b).
The market valuation of the firm then becomes

$$M_t = B_t + \sum_{t=1}^{\infty} \frac{E_t(RI_{t+1})}{(1+r)^t} \tag{5}$$

The current Market Value of the firm here is the current Book Value of the firm plus the present value of the future residual profits (Pedersen (2015), p. 92).
The Market-to-Book ratio in terms of Retained Earnings is written as

$$\frac{M_t}{B_t} = 1 + \frac{\sum_{t=1}^{\infty} \frac{E_t(RI_{t+1})}{(1+r)^t}}{B_t} \tag{6}$$

From both Market-to-Book equations 4 & 6, we can see the relationship between the Market-to-Book ratio on the one side and expected stock returns and expected earnings on the other side. Holding book equity constant, the Market-to-Book ratio increases in higher expected earnings but decreases in expected returns. Holding the Market-to-Book ratio constant, higher expected earnings imply that the expected returns must also increase, which is in line with the findings of Fama and French (2006). That implies that more profitable firms should see higher expected returns, as firms have higher earnings with constant book equity. Value firms should therefore outperform quality firms[12] due to higher expected returns[13], while profitable firms

[12]Firms with a low Market-to-Book ratio are considered Value firms, while firms with a high Market-to-Book ratio are considered Quality firms

[13]See Hou et al. (2012), who find that Value investors should go long stocks with high expected returns and short stocks with low expected returns

should outperform unprofitable firms (Novy-Marx, 2013).

3.2 The Price of Quality

Having established a relationship between the Market-to-book ratio and a firm's earnings and profitability, we derive the relationship between the Market-to-book ratio and the quality factors. This relationship is essential, as it shows if investors should be willing to pay a higher price for quality.

For the Residual Income discussed above, Asness et al. (2018b) introduce an exogenous process depending on the firm's operational free cash flows.

$$RI_t = e_t + a_t \tag{7}$$

with e_t being the sustainable earnings adjusted for the cost of book equity as above, and a_t[14] as the transitory residual income shocks. Sustainable earnings can be understood as the part of earnings that predicts future earnings and might experience growth. In contrast, the transitory shocks to retained earnings do not have a long-term impact on the firm's earnings (Asness et al., 2018b). Therefore only the sustainable residual income will experience growth, specifically in the motion

$$e_{t+1} = e_t + g_t + \epsilon^e_{t+1} \tag{8}$$

where g_t is the amount of growth of sustainable residual income and ϵ^e_{t+1} is an income innovation term with risk premium π_t. Asness et al. (2018b) show that π_t negatively correlates with the stock prices, so that higher risk premia lead to higher returns.
Both the growth and the risk premium are further assumed by Asness et al. (2018b) to be time-varying

$$g_{t+1} = \varphi_g g_t + (1 - \varphi_g)\overline{g} + \epsilon^g_{t+1} \tag{9}$$

$$\pi_{t+1} = \varphi_\pi \pi_t + (1 - \varphi_\pi)\overline{\pi} + \epsilon^\pi_{t+1} \tag{10}$$

with long-run process means given by $\overline{g}$ and $\overline{\pi}$, process persistence measures given by φ_g and φ_π and zero mean shocks given by ϵ^g_{t+1} and ϵ^π_{t+1}.
Next, Asness et al. (2018b) derive the expected sustainable residual income for the next period.

$$E_t(e_{t+1}) = \frac{1}{1 + r^f}(e_t + g_t - \pi_t) \tag{11}$$

[14] The transitory residual income shocks are defined as $a_t = \epsilon^a_t - \theta\epsilon^a_{t-1}$

The implicit relationship between the income innovation ϵ^e_{t+1} and the risk premium π_t stems from their negative covariance, which is why the risk premium has a negative sign in equation 11 above. Asness et al. (2018b) use the risk-free rate r^f instead of the required rate of return, as they use a *pricing kernel* for their economy[15].
Next, the authors iterate the expected sustainable earnings τ periods into the future. The result is the value of the sustainable earnings in τ periods in the future.

$$E_t(e_{t+1}) = \frac{1}{(1+r^f)^\tau}(e_t + \frac{\varphi_g - \varphi_g^{\tau+1}}{1-\varphi_g}(g_t - \overline{g}) + \tau\overline{g} - \frac{\varphi_\pi - \varphi_\pi^{\tau+1}}{1-\varphi_\pi}(\pi_t - \overline{\pi}) - \tau\overline{\pi}) \qquad (12)$$

Asness et al. (2018b) use equation 12 to compute the fundamental value[16] of the firm, which we consider to be our Market Value. The notation here differs slightly from Asness et al. (2018b), to be consistent with our derivation in section 3.1.

$$M_t = B_t + m^e e_t + m - m^a \epsilon^a_t + m^g(g_t - \overline{g}) - m^\pi(\pi_t - \overline{\pi}) \qquad (13)$$

From this result in equation 13, we can similarly to before derive the Market-to-Book ratio by dividing the formula with the Book value of equity B_t.

$$\frac{M_t}{B_t} = 1 + \underbrace{\frac{m^e e_t + m - m^a e^a_t}{B_t}}_{profitability} + \underbrace{m^g \frac{g_t - \overline{g}}{B_t}}_{growth} - \underbrace{m^\pi \frac{\pi_t - \overline{\pi}}{B_t}}_{safety} \qquad (14)$$

Asness et al. (2018b) find that the Market-to-Book ratio increases in residual earnings over Book value, which we have explained earlier to be the profitability. It is adjusted for accruals, confirming our observation in section 2.1.5 that high use of accruals is associated with lower profitability in the long run.
The Market-to-Book ratio also increases in growth in sustainable residual earnings, and it decreases in the risk parameter π_t. Less risk is therefore associated with a higher Market-to-Book ratio, which implies that higher safety is related to a higher Market-to-Book ratio[17]. Furthermore, Asness et al. (2018b) point out that the Market-to-Book ratio is linear in *profitability*, *growth* and *safety*, which allows us to add the specific scores together without losing the explanatory power.

This section has provided a relation between the three factors *profitability, growth* and *safety* used in Asness et al. (2018b), and the Market-to-Book ratio used as a proxy for a firms stock

[15] They argue for the necessity of this with a derivation by Feltham and Ohlson (1999).

[16] To see this result, see the valuation coefficient as $m = \frac{1+r^f}{r^{f2}}(\overline{g} - \overline{\pi})$, $m^e = \frac{1}{r^f}$, $m^g = \frac{\varphi_g(1+r^f)}{r^f(1+r^f-\varphi_g)}$, $m^\pi = \frac{\varphi_\pi(1+r^f)}{r^f(1+r^f-\varphi_\pi)}$, $m^a = \frac{\theta}{1+r^f}$ based on Asness et al. (2018b)

[17] Intuitively safety is the opposite of risk

price. It is not possible to similarly related the ESG factor to the Market-to-Book ratio. The reason for that can be found in the construction of the ESG factor, as it will be explained in section 5.1.4.

The relationship derived above is be used to determine which factors are associated with quality in our sample. After combining these quality factors into a composite quality score, quality-sorted portfolios can be created.

3.3 Capital Asset Pricing Model

In the previous section, we derived the framework for a company's market value as a function of various factors. Next, we want to show how portfolio returns can be explained. We begin by presenting different frameworks for factor investing, starting with the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965), which is considered the fundamental asset pricing model. While the model builds on the portfolio choice model constructed by Markowitz (1959), Sharpe (1964) and Lintner (1965) added assumptions to make the model portfolios mean-variance-efficient. Those two assumptions are, that investors agree on the true distribution of asset prices and that they can lend and borrow at the risk-free rate without restrictions.

The CAPM relates investment risk to the expected return of an asset. The risk is split into two parts. The first part is the systematic risk, which comes from exposure to the market and cannot be diversified away. The systematic risk is given by β. This β is defined as

$$\beta_{i,m} = \frac{Cov(r_m, r_i)}{Var(r_m)} \tag{15}$$

where the numerator is the covariance between the asset return r_i and market return r_m, and the denominator is the volatility of the market return (Campbell (2018), p.61). On average, we expect every security to have a market beta of 1, as long as the market portfolio includes the security in question. If securities have a beta of more than 1, their expected returns will be high when the market risk premium is high; if their beta is less than 1, the opposite effect takes place (Campbell (2018), p.61).

The other component of risk is the idiosyncratic risk, which can be diversified away by holding the market portfolio (Campbell (2018), p.58).
The CAPM, therefore, states that the expected return on any asset or portfolio is determined only by the systematic risk and, therefore, should be proportional to it. Further, only the systematic risk is priced, while investors are not compensated for having idiosyncratic risk

(Pedersen (2015), p. 28). The CAPM predicts that the expected return of any asset i is the sum of the risk-free rate and the exposure to the market excess return (Pedersen (2015), p.27).

Further, the Sharpe-Lintner CAPM predicts that alpha is zero for all investments because the expected asset return of an asset is solely explained by the risk premium. This was shown by Jensen (1968), who noted that the CAPM relation of beta and expected return could be extended to a time-series regression. The intercept of that regression is known as *Jensen's alpha* and is always zero.
Equation 16 is called Security Market Line *(SML)* and gives the expected return of an asset as a function of β (Campbell et al. (2008), p.50).

$$E(r_i) = r^f + \beta_{i,m}[E(r_m) - r^f] \tag{16}$$

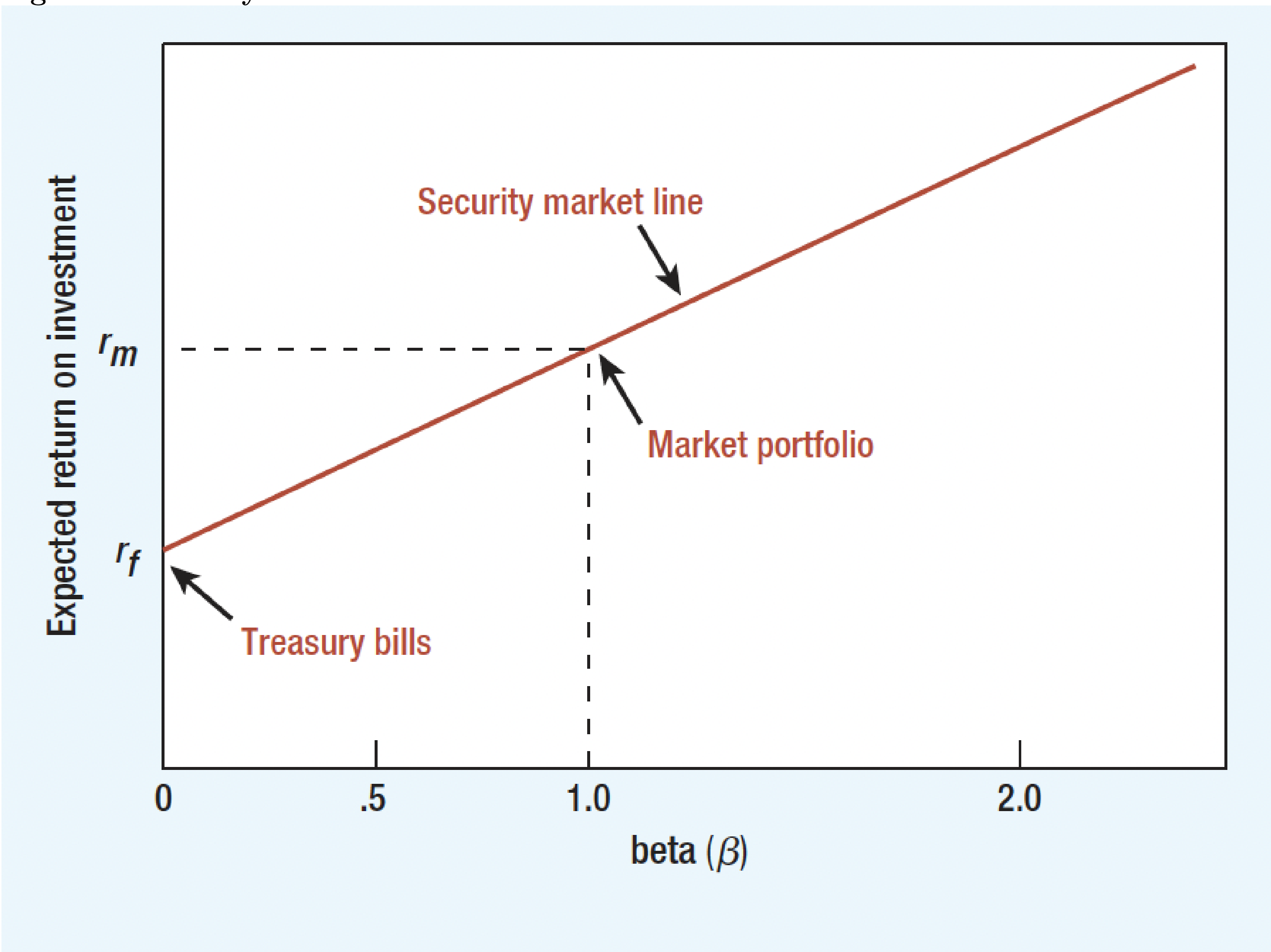
where $E(r_i)$ is the expected return of asset i, r^f is the risk-free rate, $\beta_{i,m}$ is the systematic risk measure (or market exposure) and $E(r_m)$ is the expected return of the market. Further $E(r_m) - r^f$ gives the return of the market portfolio in excess of the risk-free rate.

An asset is only correctly priced if it is on the SML, where the expected return is increasing linearly in β. If a security lies above the SML, it is underpriced as the returns are too high for the given beta. If a security lies below the SML, it is overpriced, as it generates too little returns for a given risk. In the assumed efficient market, investors would buy the underpriced asset and sell the overpriced asset, which results in both assets returning to the SML. As it can be seen in figure 16, the SML not necessarily starts at the origin of the graph, but it instead cuts the return axis at the point of the risk-free rate, which is assumed to have no exposure to the market portfolio, i.e., $\beta_{i,m} = 0$.
As discussed above, the portfolio's risk is minimized when the investor holds the market portfolio. The implication of this and the risk-adversity assumption is that the investors will diversify their portfolios until they hold all assets in the market. Investors then only differ in the weights they put on different assets (Brealy et al. (2014), p.197-202).

The CAPM framework relies on assumptions that are listed below (Campbell et al. (2008), p.47):

- All investors act rational and are risk-averse
- The investors hold the mean-variance efficient portfolio
- There are no restraints on lending and borrowing (which enables short-selling)

Figure 1: Security Market Line



Brealy, Myers, and Allen (2014) p.197

- Investors do not incur trade or transaction costs
- Information is publicly available to all investors
- Investors are not large enough to have an impact on prices

Even though the CAPM framework has been the workhorse model of asset pricing for a long time, its accuracy and assumptions are criticized and argued to make the model not applicable. Fama and French (2004) find that the CAPM model's empirical performance is bad enough to invalidate the original findings, and they argue this could stem from the simplified assumptions that are made in the original model.

For once, the market portfolio is not observable. Further, there is no clear definition of the market portfolio, whether it should include all assets in any given economy or only assets focused on certain specifics (Roll, 1977). Also, the risk-free lending and borrowing assumption does not hold in practice. This point is addressed by Black (1972), who develop a CAPM that obtains the mean-variance efficient portfolio by allowing for shorting of risky assets. Further, the CAPM does not account for liquidity risk, as evidenced by the no-trade and transaction costs assumption. The required return increases as compensation for the liquidity risk (Pedersen (2015), p.43). To account for this, Acharya and Pedersen (2005) derive the liquidity-adjusted CAPM. Lastly, the betas are not the only factors that influence returns, but rather factors such as size, price ratios, and momentum also show explanatory power (Fama & French, 2004).

While the Sharpe-Lintner CAPM is a good starting point to explain the expected returns, the assumptions are not realistic, and the model does not hold up empirically. One of the main shortcomings, that other factors influencing returns are not explained by the CAPM, has led to extensions of the CAPM by a multitude of authors, such as Fama and French (1993, 2015) or Carhart (1997). As we want to show the impact of a quality factor on average returns, only examining the CAPM returns is not applicable for us. Therefore we will further explain other asset pricing models, starting with Fama and French (1993) three-factor model.

3.4 Fama-French three factor model

As discussed above, the validity of the CAPM is highly questioned because it only allows for one factor to explain the expected returns of a security, the market risk factor. However, as Fama and French (1992) find in their analysis of stock-returns determinants, the relation between the market risk and average returns is minimal, but rather a size factor and a book-to-market equity factor explain a majority of the cross-section of average stock returns. As a result of this finding, Fama and French (1993) extend their work by establishing a time-series regression explaining average stock and bond returns with several variables. This approach follows Black et al. (1972) and differs from Fama and MacBeth (1973) and Fama and French (1992), who both aim to explain the cross-section of average stock returns.

Fama and French (1993) build on their finding in Fama and French (1992) that firms with smaller market capitalization and firms with a high Book-to-Market ratio tend to outperform the market. The corresponding portfolios introduced by Fama and French (1993) are the following:

- The portfolio related to the risk in size is called SMB (Small minus Big), which is the difference between returns on small market capitalization and big market capitalization sorted portfolios while holding the Book-to-Market ratio constant.

- The portfolio related to the risk of Book-to-Market Equity is called HML (High minus Low), which is the difference between returns on high Book-to-Market and low Book-to-Market firms while holding size constant. It is also called the value factor.

The portfolios are constructed by ranking the stocks based on their size (for SMB) or their Book-to-Market ratio (for HML) and then split into the top 30%, medium 40%, and the bottom 30%. The HML portfolios are split into a big market capitalization and a small market capitalization sample first and sorted on value after. Further, the portfolios are market value-weighted based. This procedure yields six portfolios in total. The regressions further include the market risk factor. The Fama and French (1993) three-factor model is shown below in equation 17.

$$r^e_{i,t} = \alpha_i + \beta_{i,M}\, r^e_{M,t} + \beta_{i,SMB}\, r_{SMB,t} + \beta_{i,HML}\, r_{HML,t} + \epsilon_{i,t} \tag{17}$$

where $r^e_{i,t}$ is the excess return of the portfolio, $r^e_{M,t}$ is the excess return of the market risk factor, $r_{SMB,t}$ is the return of the size risk factor and $r_{HML,t}$ is the return of the Book-to-Market Equity risk factor and $\beta_{i,M}, \beta_{i,SMB}, \beta_{i,HML}$ are the coefficients for the market, size and Book-to-Market risk factors. If those coefficients capture all the variations in expected returns, the α_i is zero for all assets. The Fama-French factors are excess returns by construction. Lastly, $\epsilon_{i,t}$ is the mean-zero regression residual or idiosyncratic risk.

In the original work in Fama and French (1993), the common variations in stock returns are found to be largely captured by the three factor-portfolio returns. Further, the results of Fama and French (1992) of a negative relation between size and average excess returns and a positive relation between Book-to-Market equity and average excess returns are confirmed. Overall, 90% of average excess returns are explained by the three-factor model, clearly exceeding the Sharpe-Lintner CAPM in performance. Therefore the Fama-French three-factor model has become a central asset pricing model, which is why we focus on it in our analysis.

3.5 Fama-French five-factor model

While the Fama-French three-factor model vastly improved the performance and predictability of expected returns compared to the CAPM, it was still argued that the model does not explain all essential factors of average returns. By using the Market-to-Book ratio, which we have derived in section 3.1, Fama and French (2015) argue that forecasts of earnings and investments are also related to expected returns. The authors choose profitability and investments as additional factors because much of the average returns related to profitability and investments are unexplained by the Fama-French three-factor model, which is backed up by many of the papers discussed in section 2, among others by Novy-Marx (2013). Fama and French (2015) choose these factors, because they are argued to be natural proxies implied by the dividend growth model and the Market-to-Book ratio.

Fama and French (2015) create the corresponding portfolios:

- The portfolio related to the risk in profitability is called RMW (Robust minus Weak), which is the difference between returns in portfolios including robust profitable and weakly profitable stocks.
- The portfolio related to the risk in investment is called CMA (Conservative minus Aggressive), which is the difference between returns in portfolios including stocks of low and high investment firms.

The Fama and French (2015) five-factor model is shown below in equation 18.

$$r^e_{i,t} = \alpha_i + \beta_{i,M}\, r^e_{M,t} + \beta_{i,SMB}\, r_{SMB,t} + \beta_{i,HML}\, r_{HML,t} + \beta_{i,RMW}\, r_{RMW,t} + \beta_{i,CMA}\, r_{CMA,t} + \epsilon_{i,t} \tag{18}$$

where $r^e_{i,t}$ is the excess return of the portfolio, $r^e_{M,t}$ is the excess return of the market risk factor, $r_{SMB,t}$ is the return of the size risk factor, $r_{HML,t}$ is the return of the Book-to-Market Equity risk factor, $r_{RMW,t}$ is the return of the profitability risk factor, $r_{CMA,t}$ is the return of the investment risk factor and $\beta_{i,M}, \beta_{i,SMB}, \beta_{i,HML}$, $\beta_{i,RMW}$, $\beta_{i,CMA}$ are the coefficients for the market, size, Book-to-Market, profitability and investment risk factors. If those coefficients capture all the variations in expected returns, the α_i is zero for all assets. Lastly, $\epsilon_{i,t}$ is again the mean-zero regression residual or idiosyncratic risk.

One very interesting result from Fama and French (2015) is that high Market-to-Book equity stocks are very likely to be profitable and to invest aggressively. The RMW factor is constructed as the average of the two robust profitability portfolio returns minus the average of the two weak profitability portfolio returns. In contrast, the CMA factor goes long the two portfolios with conservative investment and short the two aggressive investment portfolios. Both factors are created similarly to the HML factor by being sorted in the first step by the size of the firm's market capitalization. The sorting with respect to size leads to the property that HML, RMW, and CMA are neutral with respect to firm size.

Finally, while a *momentum* factor based on Jegadeesh and Titman (1993) was integrated into Fama and French (1993) three-factor model by Carhart (1997) to create his four-factor model, it is not found to add significant variations to the average returns by Fama and French (2015). We therefore do not consider Carhart (1997) four-factor model in our thesis.
One of the main results of Fama and French (2015) is, that the high Book-to-Market factor HML, also called value factor, does not add to the variation in average returns in the five-factor model. Fama and French (2015) argue that the HML factor returns are absorbed by the RMW and CMA factors, making the HML factor redundant. The five-factor model improves the performance of the three-factor model and adds exposure to profitability, which is very interesting

for us as we include profitability in our quality score. We analyze our quality score also in a Fama-French five-factor model environment.

4 Data

We have now established a theoretical framework, where we have discussed possible quality metrics and decided on which factors we will examine for a link to higher stock prices.
This section introduces the data we use to analyze the German market.

4.1 Data sources

This thesis has predominantly used accounting data from *Compustat* provided through the *Wharton Research Data Services (WRDS)*[18] and financial data from *Datastream* provided through the *CBS Library Datalab*. The corresponding data for the German market needed for our analysis is included in the *Compustat Global - Fundamentals Annual* database. We have chosen to use annual companies' financial and accounting data to align with our yearly portfolio rebalancing approach. In addition, the use of annual data instead of quarterly data is preferable, as all listed German companies are required to publish an annual report, whereas the publication of a quarterly report is not mandatory (§242 German Commercial Code).[19]

We search the database for annual accounting data for active and inactive German firms by selecting the country code *DEU*. Including inactive companies also assures a complete overview of the German market at any point in time within our sample. In addition, we select the industry format *INDL* to ensure that financial firms and banks are excluded from the sample. Financial companies do not sell goods, which results in the absence of accounting data such as sales figures or cost of goods sold, which are relevant for calculating some quality factors. Moreover, financial companies are often more levered than non-financial companies. These high leverage levels would indicate financial distress in non-financial companies and therefore make comparability between financial and non-financial companies difficult, as leverage is a crucial factor in safety scores (Fama & French, 1992). Most of the literature either excludes financial firms, such as Chen and Novy-marx (2011), Novy-Marx (2013), Fama and French (1992), Kozlov and Petajisto (2013), or considers them separately, as in Novy-Marx (2014a), for the reasons mentioned above. We obtained data for the fiscal year endings from 1999 to 2020, resulting in an initial sample size of 1182 firms for which accounting data is available.

[18]The data can be downloaded at `https://wrds-www.wharton.upenn.edu/`
[19]`https://www.gesetze-im-internet.de/hgb/__242.html`

The ISIN[20] codes of the relevant companies relevant were used to download the monthly closing share prices and the corresponding market values from the *Datastream* database. This financial data is relevant for calculating some quality scores and the portfolio constructions performed at a later stage. In addition, we downloaded the *Thomson Reuters* ESG score for all German firms with an ESG score available from the *Datastream* database, again excluding financial firms.

The analyses and calculations in this paper were performed using the statistical software package R (R Core Team, 2020). It is necessary to download the relevant packages for the code, such as the *quantmod* package from Ryan and Ulrich (2020), the *PerformanceAnalytcis* package from Peterson and Carl (2020), the *corrplot* package from Wei and Simko (2021), the *datatable* package from Dowle and Srinivasan (2021) and the *writexl* package from Ooms (2021). In addition several packages from tidyverse are needed (Wickham et al., 2019). All tables showing output from R were created with the R package *Stargazer* (Hlavac, 2022).
The R code files and corresponding Excel spreadsheets are included in a separate appendix to this thesis to allow reproducibility of all calculations, graphs, and tables.

4.2 Data clean-up

The accounting data download contains all relevant figures needed to calculate the quality factors for profitability, growth, and safety. However, before these factors can be calculated, the data must be cleaned to ensure that all required information is available and that the companies' accounting figures can be compared.

As mentioned in section 4.1, financial firms and banks must be excluded from the sample to ensure that only firms for which all required accounting data is available are compared. We have included the GIC sector code in the download to determine the company's industry sector. The Global Industry Classification Standard (GICS) was developed in 1999 to classify companies into specific industries, determined by their primary business operations. A company can belong to one of eleven possible sectors. These sectors are *Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities* and *Real Estate* (MSCI, 2022).
Therefore, as a first step, we filter out data with the GIC sector number *40*, the GIC number for the financial sector. This yields a further 22 companies still included in the download belonging to the financial sector. These companies are excluded from the sample for the reasons mentioned above.

[20]ISIN is short for International Securities Identification Number

The downloaded data is in a panel format, i.e. each row represents the accounting data of one fiscal year for a company. In order to measure the performance of a company, it is necessary to rank the metrics underlying the different quality factors every year. Therefore, only one financial report can be contained per fiscal year for each company, which is violated in a few instances. In our sample, most companies end their fiscal year at the end of December. Therefore the annual reports of all companies are aligned to the 31st of December. If the sample contains two observations for a company for the same fiscal year, the latter is used, while the earlier observation is excluded from the sample.

In addition, our sample covers a company's fiscal year only if all data is available to calculate all proxies for the quality factors *profitability, growth* and *security*. While it is possible to calculate the profitability and safety scores each year, this is not the case for the growth scores. To calculate the company's growth scores by the definitions from Asness et al. (2018b), six years of prior accounting data are required. Therefore, only companies with seven or more years of accounting data are included in the sample. If fewer observations are available, those companies are excluded. Therefore, companies that were dissolved in the early 2000s are excluded, as the first annual reports included in the sample date back to 1999. In addition, companies that went public after 2014 are not part of the sample.

As we will show in section 5.1.1, calculating the ratios ROA, CFOA, GPOA, leverage, and Low Accruals involves dividing by the company's total assets. Since dividing by zero is not possible, all observations that contain either zero or no information are excluded from the sample. The procedure is also used if total common ordinary equity, used as a proxy for book equity, contains either zero, a negative value, or no information. This is necessary since book equity is the denominator for calculating ROE and the Market-to-Book value. The same applies to zero values for a company's total liabilities since this accounting ratio is used as a denominator in calculating the O-score. In the literature, e.g. Chen and Novy-marx (2011), Asness et al. (2018a), Hsu et al. (2018), or Kozlov and Petajisto (2013), it is common to include only the firms in the sample that have a positive book and market value of equity.
Furthermore, calculating a company's gross profit and cash flows requires revenues. Therefore, all years without revenue figures are excluded from the sample. The missing values for the remaining accounting variables, which have less impact on the calculations, are replaced with zero. This data cleaning process is necessary to ensure that we do not obtain NA values in the calculations of the quality factors and the firm value.

As a final step, we need to ensure that it is possible to invest in a company after being ranked for a given fiscal year. First, only companies listed on a stock exchange can be included in the sample. Otherwise, it is impossible to construct portfolios that include these companies, as their stocks can not be traded. Second, only companies with an ISIN code can be included in the sample to ensure that the correct stock price is associated with the company in the accounting sample. Third, even if a firm is listed on the stock market, we need to ensure that it is listed at the correct time. As in Fama and French (1992), we match all accounting data ending within fiscal year t-1 to be able to rank the firms each year. As all German listed companies are required to publish their annual financial statements within the first four months of the year (§325 German Commercial Code[21] & §264d German Commercial Code[22]), we start our portfolio construction in May of each year, two months earlier than Fama and French (1992). When classifying a company for a given year t-1, it is necessary to check whether the company is still listed on the stock exchange in May of year t. Finally, only companies with a market capitalization of more than €1 million are included to ensure an appropriate minimum company size.

After completing the data cleaning, we have 653 unique companies and an average of 460 companies per year. A list of these 653 companies is shown in figure 14 in the appendix. This is a solid database to calculate the different quality proxies. This database will, from here on, be referred to as the benchmark database. Table 1 shows the descriptive statistics of all accounting variables for the fiscal year endings from 1999 to 2020. Since the first financial reports are aligned to the end of 2005, the first ranking of firms will take place in May 2006. Figure 2 shows the number of companies included in the ranking process over the years in our scope. The sample size is volatile during our sample period, peaking with 435 companies in 2012 and showing a continuous decline since, with the lowest number of companies included of 346 in 2021. The calculation of the growth measures and the excess portfolio returns requires the use of a risk-free rate. Since it was impossible to obtain reliable data for short-term German government bonds over a longer period, we decided to use the Euribor rate, which was first published in 1999, when our sample started.[23] The 12-month Euribor rate is used for the growth measure calculations. The excess returns are calculated monthly. Therefore, we use the 1-month Euribor rate here. The development of the two rates over the years can be seen in figure 3. Since Euribor rates are published per annum, the 1-month Euribor rate must be divided by 12 when we use the risk-free rate to calculate the excess return.

As one of the objectives of this thesis is to show the impact of the ESG score on stock prices, the next step is to create a separate accounting database. The same data cleaning process is performed as for the benchmark database. The only difference is that the new database

[21] https://www.gesetze-im-internet.de/hgb/__325.html

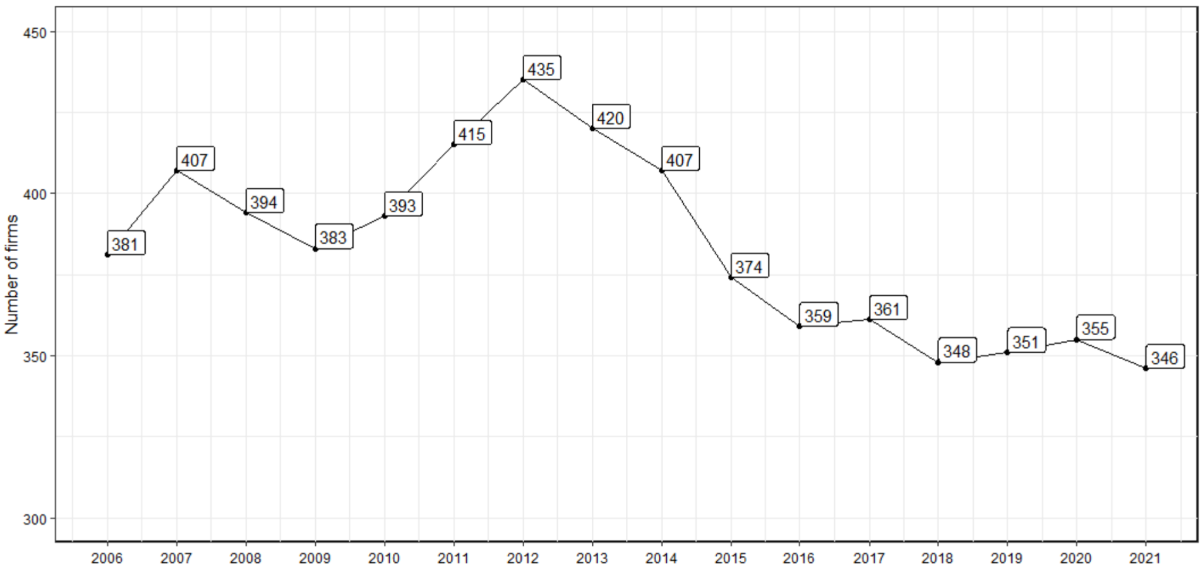
[22] https://www.gesetze-im-internet.de/hgb/__264d.html

[23] The data can be downloaded at https://www.global-rates.com/en/

Table 1: Descriptive Statistics Full sample

in MEUR	N	Mean	St. Dev.	Min	Max
Current Assets (CAT)	10,047	1,818.53	10,007.69	0.01	242,447
Assets Total (AT)	10,047	4,345.71	22,224.77	0.33	497,114
Capital Expenditures (CAPEX)	10,047	209	1,264.63	0.02	32,538
Common Ordinary Equity	10,047	1,186.51	5,513.95	0.02	127,049
Cost of Goods Sold (COGS)	10,047	2,053.47	9,658.68	−15.29	157,692
Debt in Current Liabilities Total	10,047	409.03	3,573.96	0	89,757
Long Term Debt Total	10,047	838.01	5,228.90	0	121,284
Depreciation and Amortization (DPA)	10,047	171.17	902.09	−20	23,447
EBIT	10,047	216.74	1,049.21	−11,606	21,173
Current Liabilities (CLT)	10,047	1,463.86	8,770.34	0	241,398
Liabilities Total (LT)	10,047	3,076.87	16,819.09	0.03	368,331
Pretax Income (PTI)	10,047	174.13	1,023.53	−26,786	25,493
Retained Earnings (RE)	10,047	611.38	4,282.69	−36,859	100,772
Revenue Total	10,047	3,255.78	13,911.59	0.01	252,632
Working Capital (WC)	10,047	354.67	2,208.51	−40,671	60,191
Dividends	10,047	50.98	278.26	0	7,185.90
Income Before Extraordinary Items (IB)	10,047	111.01	766.71	−24,587	21,717

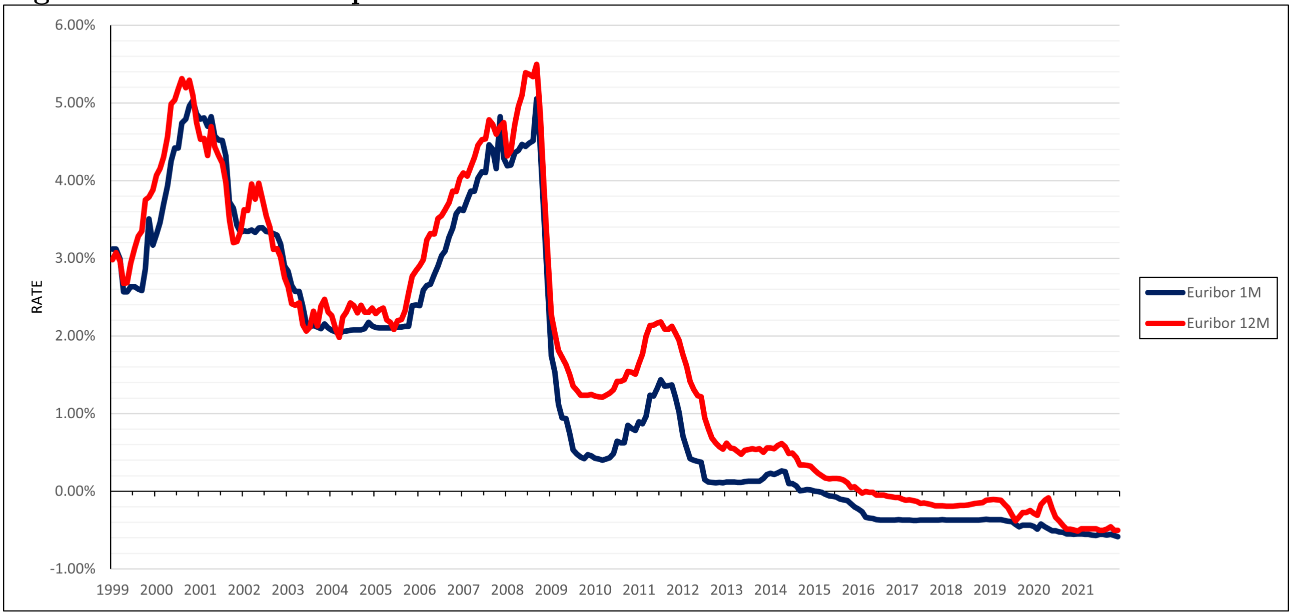
Figure 2: Sample size Benchmark scenario



contains only those companies for which an ESG score is available. This is necessary to ensure that we are consistent with the previous approach of only considering a company's fiscal year if it is possible to calculate all quality metrics. As a result, our database is shrinking significantly. A list of all included companies is shown in figure 15.

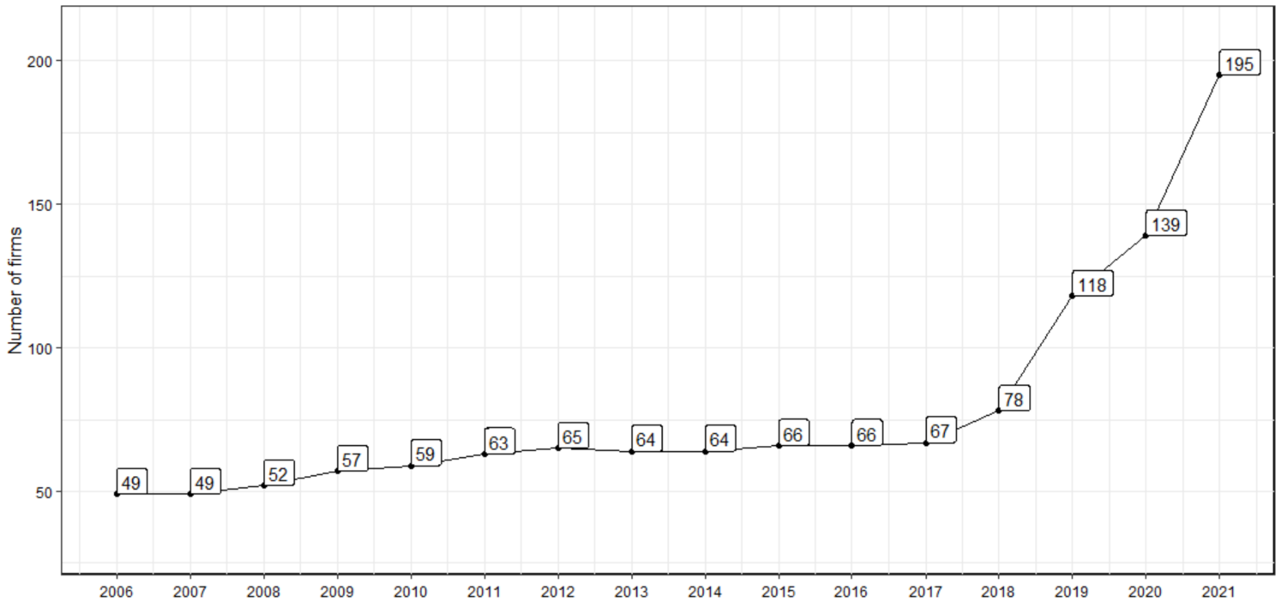
There are two main reasons for this. First, many companies have no ESG score, which leads to a complete exclusion of the company. Second, the companies that received an ESG rating did

Figure 3: Euribor rates per annum



so predominantly in recent years, resulting in a sample size of 49 companies for the first ranking in 2006 and 195 companies for the final ranking in 2021. Figure 4 shows that, especially from 2018 to 2021, the availability of ESG data has risen exponentially. This can be attributed to investors' increased focus on ESG factors during these years. More investors are valuing an ESG score[24], so companies are incentivized to publish the necessary information.

Figure 4: Sample size ESG firms



[24]See Pedersen, Fitzgibbons, and Pomorski (2021), who find that a specific type of investor is willing to accept a lower Sharpe ratio if the firm has an ESG score.

5 Methodology

After describing our data sample and the specifications needed for our analysis, we will now define our factors and the measures found to be proxies for quality factors in section 2.

5.1 Quality scores and how to rank

We use the benchmark database to calculate a quality score composed of a profitability score, a growth score and a safety score. The smaller sample can be used to include the ESG score in our analysis. This thesis aims to show that the factors individually and combined reflect quality within a company and that our quality score thus represent an investment opportunity. There are different approaches for evaluating the quality measures, for example, in Bouchaud et al. (2016) or Norges Bank (2015). To rank, compare, and combine the different quality measures, we use the approach of Asness et al. (2018b). First, we rank the quality factors of each company for a given fiscal year cross-sectionally in ascending order. While Asness et al. (2018b) has managed to rank the quality factors of a company monthly, we choose a yearly ranking approach. To make these ranks comparable and aggregate them, we calculate a measure called *z-scores*. If x is the variable of interest and r is the corresponding vector of ranks $r_x = rank(x)$ with cross-sectional mean $\overline{r}_x$ and standard deviation $\sigma(r_x)$, the z-score of x at year t can be calculated as:

$$z_x = \frac{[r_x - \overline{r}_x]}{\sigma(r_x)} \tag{19}$$

This re-scaling of the ranks is done to obtain cross-sectional ranks with a cross-sectional mean of zero and a cross-sectional standard deviation of one.
After establishing the approach behind classifying the accounting data and using it to create ranks, we will dive into the calculation of the proxies for the quality factors that we have chosen based on the assessment made in section 2.

5.1.1 Profitability

Including five different profitability metrics and subsequently averaging them into one profitability score is intended to reduce noise while focusing on the sustainable part of corporate profits relative to book values. From this point on, we will use the ratio between net income (NI) and book equity (B)

$$\frac{NI_t}{B_{t-1}} - r^f \tag{20}$$

of companies instead of the ratio between residual income (RI) and book equity

$$\frac{RI_t}{B_{t-1}} \tag{21}$$

as they only differ by the risk-free interest rate r^f (Asness et al., 2018b).

This is particularly important as we need a company's net income to calculate ROE and ROA and the corresponding growth measures. For Net income, we use the *Compustat* item *Income before extraordinary items* (IB), similar to the approach of Asness et al. (2018b) and Chen and Novy-marx (2011). ROE is calculated as in Asness et al. (2018b) and Bouchaud et al. (2016) and return on assets (ROA) as in Asness et al. (2018b) and Mohanram (2005). In order to calculate the book equity of a company, one must know the shareholders' equity of a firm, which can be determined in various ways. Asness et al. (2018b) uses either stockholders' equity as a proxy or the sum of common ordinary equity and preferred stock for book equity. The same approach is used in Chen and Novy-marx (2011), Asness et al. (2018a) and Novy-Marx (2013, 2014a). Since book equity is defined as the difference between stockholders' equity and preferred stock, we can use common equity instead of book equity. This ensures that we use the same base for all companies.

$$ROE = \frac{Net\ Income}{Book\ Equity} \tag{22}$$

$$ROA = \frac{Net\ Income}{Assets\ Total} \tag{23}$$

The calculation of the CFOA requires the Cash Flow of a firm which is calculated as follows:

$$Cash\ Flow = NI + DPA - \Delta WC - CAPEX. \tag{24}$$

where DPA is Depreciation & Amortization, ΔWC is the change in Working Capital, and CAPEX is the firms Capital Expenditure.
If we divide the cash flow (CF) by total assets (AT), we get the quality factor CFOA as in Asness et al. (2018b), Bouchaud et al. (2016) and Kozlov and Petajisto (2013).

$$CFOA = \frac{Cash\ Flow}{Assets\ Total} \tag{25}$$

To obtain the GPOA, we first subtract the cost of goods sold (COGS) from the total revenue to get the gross profits (GP). The quality factor GPOA can then be calculated similiar to Asness et al. (2018b) and (Novy-Marx, 2013).

$$GPOA = \frac{Gross\ Profits}{Assets\ Total} \tag{26}$$

The final profitability score, low accruals (ACC), is again calculated as in Asness et al. (2018b).

$$ACC = -\frac{(\Delta\, WC - DPA)}{Assets\ Total} \tag{27}$$

Descriptive statistics of net income, cash flow, gross profits and book equity relevant for the calculation of profitability ratios, can be seen in table 2.

Table 2: Descriptive Statistics Profitability

Statistic	N	Mean	St. Dev.	Min	Max
Net Income (NI)	10,047	111.01	766.71	−24,587	21,717
Cash Flow (CF)	10,047	73.32	1,761.00	−88,456	64,487
Gross Profits (GP)	10,047	1,202.32	5,024.50	−5,631.00	94,940
Book Equity (B)	10,047	1,186.51	5,513.95	0.02	127,049

Descriptive statistics for the five profitability metrics are shown in table 3. The difference in the number of observations in tables 2 and 3 is due to the fact that at least six years of accounting data must be available for the calculation of growth scores. Therefore, fewer scores can be calculated than possible if only profitability scores were calculated.

Table 3: Descriptive Statistics Profitability Scores

Statistic	N	Mean	St. Dev.	Min	Max
ROE	6,129	−0.010	0.636	−27.634	4.113
ROA	6,129	0.015	0.134	−1.773	0.679
CFOA	6,129	0.013	0.165	−3.112	2.704
GPOA	6,129	0.419	0.278	−0.585	4.416
ACC	6,129	0.039	0.147	−1.908	2.674

To obtain the combined profitability z-score, the z-scores of the individual profitability scores are averaged and aggregated as in Asness et al. (2018b).

$$Profitability = z(z_{ROE} + z_{ROA} + z_{CFOA} + z_{GPOA} + z_{ACC}) \tag{28}$$

5.1.2 Growth

As shown above, Asness et al. (2018b) managed to collect definitions of the profitability proxies further used in several other papers. As the growth factors are based on the profitability factors, it is consistent that we use the growth definitions as in Asness et al. (2018b). As the profitability factors should reflect the sustainable part of a company's profits, the growth factors will indicate how sustainable these profits are over time. Due to the volatility of profits, a five-year period is used to test the sustainability of growth (Asness et al., 2018b). As mentioned in section 4.2, six years of accounting data are required to calculate these growth measures, shown by the lag t-6 used in the equations below.

While the difference between net income and residual income does not change results when calculating the profitability factors, it is necessary to distinguish when calculating the growth factors (Asness et al., 2018b). The growth factors are calculated for all profitability factors except the low accrual metric. The five-year growths in residual ROE, ROA, CFOA, and GPOA are calculated as follows:

$$\Delta ROE = \frac{(NI_t - r^f_{t-1}B_{t-1}) - (NI_{t-5} - r^f_{t-6}B_{t-6})}{B_{t-5}} \tag{29}$$

$$\Delta ROA = \frac{(NI_t - r^f_{t-1}AT_{t-1}) - (NI_{t-5} - r^f_{t-6}AT_{t-6})}{AT_{t-5}} \tag{30}$$

$$\Delta CFOA = \frac{(CF_t - r^f_{t-1}AT_{t-1}) - (CF_{t-5} - r^f_{t-6}AT_{t-6})}{AT_{t-5}} \tag{31}$$

$$\Delta GPOA = \frac{(GP_t - r^f_{t-1}AT_{t-1}) - (GP_{t-5} - r^f_{t-6}AT_{t-6})}{AT_{t-5}} \tag{32}$$

Descriptive statistics for the four growth metrics are shown in table 4.

Table 4: Descriptive Statistics Growth Scores

Statistic	N	Mean	St. Dev.	Min	Max
ΔROE	6,129	0.138	1.329	−27.550	37.797
ΔROA	6,129	0.037	0.359	−12.935	5.641
$\Delta CFOA$	6,129	0.002	0.469	−11.139	9.669
$\Delta GPOA$	6,129	0.037	0.789	−5.427	16.838

The combined growth z-score can be obtained using the same averaging and aggregation approach as for the profitability factors similiar to Asness et al. (2018b).

$$Growth = z(z_{\Delta ROE} + z_{\Delta ROA} + z_{\Delta CFOA} + z_{\Delta GPOA}) \tag{33}$$

5.1.3 Safety

The third factor in our benchmark scenario is the safety factor. It is composed of Earnings Volatility (EVOL), leverage (LEV), Ohlson (1980)´s *O-score* and Altman (1968)´s *Z-score*. The EVOL factor, i.e. the standard deviation of the annual return on equity of the last five years, is the safety factor with the clearest connection to profitability and growth factors. In Asness et al. (2018b), this factor was calculated using quarterly data for the US market. However, since we only use annual accounting data here, we calculate the volatility of the annual ROE over a time window of five consecutive years, similarly to Asness et al. (2018b) in their global sample.

As with the profitability and growth scores, we also want to sort the safety values in ascending order. However, higher volatility of the ROE is not a sign of a safer company. Therefore, we multiply the calculated EVOL by -1 to ensure that the highest value is assigned to the safest firm and therefore receives the highest rank, thus ensuring consistency in our ranking. The same applies to the second safety factor, leverage. The higher the leverage of a company, the riskier it is. Therefore, we multiply the calculated leverage factor by -1 to ensure a correct ranking. To calculate a similar leverage factor as in Asness et al. (2018b) or Kozlov and Petajisto (2013), the total company debt is needed. It can be obtained by summing the long-term debt and the debt in current liabilities. The leverage factor can then be calculated by dividing the total debt by total assets:

$$LEV = -\frac{Debt}{Assets\ Total} \tag{34}$$

The more classic measures of safety are Ohlson (1980)´s *O-score* and Altman (1968)´s *Z-score*, both of which measure a firm´s risk for bankruptcy. Ohlson (1980)´s *O-score* incorporates several economic factors and decision variables, as seen in equation 35.

$$O - score = -\begin{pmatrix} -1.32 - 0.407 * log(\frac{ADJAT}{CPI}) + 6.03 * \frac{Debt}{ADJAT} - 1.43 * \frac{(CAT-CLT)}{ADJAT} \\ +0.076 * \frac{CLT}{CAT} - 1.72 * Dummy_1 - 2.37 * \frac{NI}{AT} - 1.83 * \frac{PTI}{LT} \\ +0.285 * Dummy_2 - 0.521 * \frac{(NI_t - NI_{t-1})}{(|NI_t| + |NI_{t-1}|)} \end{pmatrix} \tag{35}$$

In total, Ohlson (1980)´s *O-score* is composed of nine different factors. The first factor $\frac{ADJAT}{CPI}$ should correspond to the size. Adjusted assets (ADJAT) are a modification of a company's total assets divided by its market equity and book equity (equation 36). Campbell et al. (2008)

uses this adjustment to account for outliers and to ensure that total assets are not too close to zero.

$$Adjusted\ Assets = Assets\ Total + 0.1 * (Market\ Equity - Book\ Equity) \tag{36}$$

As we have aligned all fiscal year-end accounting variables, including book equity, to the end of December, we also use the corresponding market values at the end of December. It follows that we use for example a company's market capitalization for the end of December, even though the company's fiscal year ended in September. This approach is consistent with the one taken by Fama and French (1992). On the one hand, they show in their paper that using market equity at the end of the fiscal year instead of market equity at the end of December has little impact on their calculations. On the other hand, they point out that using market equity at the end of the fiscal year also creates problems because part of the cross-sectional variations in the Market-to-Book ratio is due to fluctuations in the overall market during the year. Thus, if there is a general decline in all stock prices during a given year, the Market-to-Book ratios measured later in the same year would be higher than the corresponding ratio measured at the beginning of the year (Fama & French, 1992).

The *O-score* was developed in 1968, so the Consumer Price Index (CPI) used in its calculation assumes a base value of 100 in 1968. To be consistent in our calculation of the *O-score*, we also index the German CPI to 1968. The German CPI can be downloaded from the German Federal Statistical Office[25]. The CPI contains the prices of all services and goods purchased by German households for consumption and can therefore be seen as a proxy of inflation. Due to the reunification of Germany in 1990, a combined CPI value has existed since 1991, whereas separate publications for the two German territories existed until then. (FederalStatisticalOffice, 2022). For this reason, an exact indexation to 100 in 1968 is not easy to accomplish. In order to ensure an adequate calculation of the *O-score*, several intermediate calculations were made.

Overall, the nine factors of the *O-score* are defined as follows:

1. $log(\frac{ADJAT}{CPI})$ is the fraction of the CPI to total firm adjusted assets
2. $\frac{Debt}{ADJAT}$ corresponds to the fraction of the debt with the total assets in the firm.
3. $\frac{(CAT-CLT)}{ADJAT}$ can be seen as the division of working capital by total assets. Working capital is calculated as the difference between total current assets (CAT) and total current liabilities (CLT).
4. $\frac{CLT}{CAT}$ is the division of current liabilities by current assets.

[25] The data can be downloaded from: `https://www.destatis.de/EN/Home/_node.html`

5. The $Dummy_1$ takes a value of 1 if total liabilities exceed total assets and zero otherwise.

6. $\frac{NI}{AT}$ is net income divided by total assets.

7. $\frac{PTI}{LT}$ measures the operational funds relative to a firm's total liabilities (LT). For those funds, the proxy Pretax Income (PTI) is used.

8. The $Dummy_2$ takes a value of 1 if the NI was negative for two consecutive years and zero otherwise.

9. $\frac{(NI_t - NI_{t-1})}{(|NI_t| + |NI_{t-1}|}$) measures the change in NI.

The negative sign in front of the parenthesis ensures correct sorting, as explained above, since a more negative *O-score* corresponds to a safer company.

Altman (1968)'s *Z-score* is another measure for bankruptcy risk probability (equation 37). As described by Asness et al. (2018b), it is a weighted average of

1. Working Capital (WC)

2. Retained Earnings (RE)

3. Market Equity (M)

4. Earnings Before Interest and Taxes (EBIT)

5. Sales

Similar to the *O-score*, the weights to the various factors also differ.

$$Z - score = \frac{(1.2WC + 1.4RE + 3.3EBIT + 0.6M + Sales)}{AT} \tag{37}$$

Altman (1968) motivates the inclusion of the different factors as follows. A company that suffers an operating loss will likely have a shrinking CAT. Therefore WC, defined as the difference between CAT and CLT, could be an early indicator of discontinuance of operations. By including RE, the firm's age is taken into account, as a newly founded company has not yet had the time to generate cumulative profits. Newer companies must first demonstrate that they can stay in business for an extended period and are therefore considered more at risk of insolvency. Continuously achieving a high EBIT vastly improves the company's chance to stay in business. As a result, the EBIT ratio can be considered the true productivity factor of a company's assets, excluding tax and interest payments. The inclusion of sales reflects a company's ability to generate revenue and its ability to operate in a competitive environment (Altman, 1968).

Our inclusion of the market equity factor differs from Altman (1968) 's original work but uses the same approach as in Asness et al. (2018b). While Altman (1968) calculates the market equity factor relative to the book value of total debt, we use an adjusted approach and divide the market equity factor by total assets. Since a higher Altman (1968) *z-score* corresponds to a safer company, the score can be used without adjustments in our ascending order approach. Descriptive statistics for the four safety metrics are shown below in Table 5.

Table 5: Descriptive Statistics Safety scores

Statistic	N	Mean	St. Dev.	Min	Max
EVOL	6,129	−0.202	0.592	−12.611	−0.001
LEV	6,129	−0.184	0.163	−0.939	0.000
O-score	6,129	0.534	2.087	−21.770	15.421
Z-score	6,129	2.132	2.370	−53.939	14.799

The combined safety z-score can be obtained using the same averaging and aggregation approach as for the profitability and growth factors.

$$Safety = z(z_{EVOL} + z_{LEV} + z_{O-score} + z_{Z-score}) \tag{38}$$

5.1.4 ESG

Next,we will discuss the definition of the ESG factor, the intuition behind the specific metrics within the factor, and the calculations needed to construct the factor.
Our ESG score data stems from the Refinitiv Eikon ESG database, one of the most comprehensive ESG databases covering over 80% of the global market capitalization, including 500 different ESG metrics. The database covers over 11000 global companies, with data going back to 2002. The Dax 40, Germany's main stock market index, has been present in the database since its inauguration in 2002. We were able to access the database through the *CBS Library Datalab*. While the database features up to 12 different ESG-related scores within a given year, we will focus on the database's main score, the Refinitiv ESG score. The following information regarding the calculation of the ESG score comes from Refinitiv (2021). The ESG score consists of 10 different categories with 186 total metrics. Those 10 categories are split into Environmental, Social, and Corporate Governance factors.

Table 6 shows the distributions of these 186 metrics within the 10 ESG categories. All information was obtained from public company disclosures. The ESG score is the relative sum of the category weights, where the pillar weights are normalized between 0% and 100%. 0%

Table 6: ESG categories

ESG Score	Environmental	Social	Governance
Resource use	20		
Emissions	28		
Innovation	20		
Workforce		30	
Human rights		8	
Community		14	
Product responsibility		10	
Management			35
Shareholders			12
CSR strategy			9

is the worst achievable percentage (called "ESG laggards"), and 100% is the best achievable percentage (called "ESG leaders").
Refinitiv uses both boolean and numeric data points in the calculation. Each boolean data point is assigned either a positive or negative polarity, indicating whether a higher value has a positive or negative association. For example, answering "Yes" to whether an emissions reduction policy is in place is seen as positive. In contrast, answering "Yes" to whether environmental controversies are present is seen as negative.
If positive polarity questions are answered "Yes", a value of 1 is assigned and a 0 otherwise. If negative polarity questions are answered "Yes", a value of 0 is assigned and a 1 otherwise. A relative percentile ranking approach is conducted for numeric data, but only if the company reports that data point. The questions again have a positive or negative polarity and are ranked respectively.

The categories scores are calculated with a percentile rank scoring methodology.
The important metrics for the calculations are:

- number of companies with a worse value than the company in scope (X1)
- number of companies with same value included in the current one (X2)
- number of companies with a value (X3)

$$score = \frac{X1 + \frac{X2}{2}}{X3}$$

A step-by-step calculation is described by Refinitiv (2021) in the following matter:

1. For each category, all related metrics are taken, and the corresponding values are extracted

2. The numeric metrics are taken only if the company reported them

3. Numeric values are calculated for the Boolean metrics

4. Percentile score calculations are used for the measures

As the ESG score is calculated by Refinitiv (2021) in a sophisticated and advanced procedure, we will incorporate the ESG score into our quality regressions. We rank the companies according to their ESG score and calculate z-scores as in Asness et al. (2018b). This allows us to compare the ESG score with the other quality factors in our small sample. The ESG factor is therefore defined as $ESG = z(ESG)$.

Figure 5: Top 10 firms with ESG score

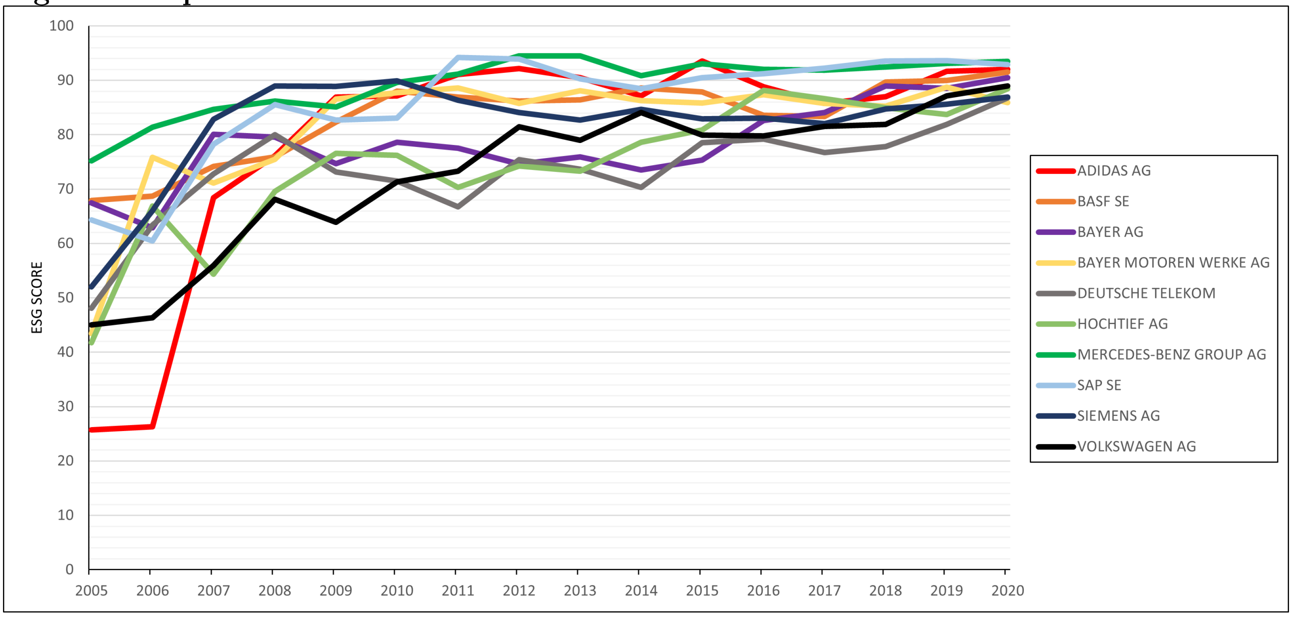


Figure 5 shows the firms with the ten highest ESG scores in 2020[26]. The development of the graphs can be explained by the calculation of the ESG scores discussed above. All firms have had a score since the start in 2005, which speaks to the cumulative effect of the scoring methodology. Having an ESG score in the previous years increases the score in the current year. These firms are rewarded with a higher ESG rating by being included longer in the ESG sample. These ten firms also tend to have very high market capitalizations.

5.1.5 Quality

The aggregation of our individual quality factors culminates in our combined quality score, which forms the base of our investment strategies in section 6.2.

[26]The ESG score for a given year is published within the next year, f.e. the ESG score of 2020 is published in 2021.

Similar to Asness et al. (2018b) our goal for the combined quality score is to include the factors that investors are willing to pay a higher price for. This approach assures that a higher quality factor score implies higher firm quality. This connection is important because it allows us to sort our portfolios for quality. If a factor does not positively impact our Market-to-Book ratio, we therefore not include it in our quality score.

The methodology behind constructing the combined quality score is the same as for the construction of the individual quality factor scores described in equations 28, 33 & 38. We combine the individual *z-scores* of factors found to be associated with higher quality in section 6.1 into a *z-score* for the combined quality score.

5.2 Quality regressions

Before we can build portfolios based on our quality scores, we must first determine whether investors are willing to pay a higher price for high-quality stocks than for low-quality ones. Using the methodology of section 3.2, which connects the Market-to-Book ratio to the factors, we will examine if the data matches the theory.

As in Asness et al. (2018b), we define the stock price as

$$P_t^i = log(M/B)_t^i \tag{39}$$

which is consistent with the derived dividend discount model.

To calculate the Market-to-Book ratio

$$\frac{M}{B} = \frac{Market\ value}{Book\ Equity} \tag{40}$$

we need the book value of equity as well as the market value of equity for the company. Similarly to calculating the profitability and growth factors, common ordinary equity is used as a proxy for book equity.

The logarithm of the market-to-book ratio is used as it eases the interpretation of coefficients.

$$Market\ Value = Shares\ Outstanding * Current\ Market\ Price \tag{41}$$

The market values can be obtained from the *Datastream* database. Since all financial reports must be published in the first four months of a year[27], companies are ranked in May. Therefore, we use a company's market value at the beginning of May as the numerator and the company's book equity from the previous fiscal year as the denominator. This procedure is consistent with Asness et al. (2018b). The use of the market value at the end of the fiscal year aligned to each

[27]§325 German Commercial Code

December changes the results only slightly.

To check whether high-quality stocks command a higher price, we run cross-sectional regressions of a company's stock price on the factor z-scores consistent with Asness et al. (2018b). We look at different scenarios of regressing the stock price on our factor scores profitability, growth, safety, and ESG. Further, we regress the stock price on our combined quality score, which is comprised of the individual quality factors. The proxy Z_t^i in equation 42 represents the various z-scores we used in the regressions, the factors $Profitability_t^i$, $Growth_t^i$, $Safety_t^i$, ESG_t^i and $Quality_t^i$. Further, all regressions, unless explicitly stated otherwise, analyze our benchmark sample and not the smaller ESG sample. The small sample approach is only taken when showing the ESG score calculations and regressions.

$$P_t^i = a + b\ Z_t^i + \epsilon_t^i \tag{42}$$

We will focus on our combined quality score, as we show throughout the thesis that quality consists of multiple factors. As in Asness et al. (2018b) we also control for a size factor and dividends in the cross-sectional quality regressions, as seen below in equation 43.

$$P_t^i = a + b\ Quality_t^i + controls + \epsilon_t^i \tag{43}$$

First, we control for size, in line with the results of Hou and Van Dijk (2019), who find that large companies experience positive profitability shocks. Profitability and, as a result, quality should therefore be correlated to firm size, agreeing with Fama and French (2006). Further, profitability is linked to a high Market-to-Book ratio, indicating that larger firms have higher Market-to-Book ratios if they are profitable. As in Asness et al. (2018b) we calculate the size factor as the logarithm of the market capitalization of the corresponding year as a z-score like the other factors to allow for a straightforward interpretation. Including a dividend dummy with value 1 for firms paying dividends in the previous year and 0 otherwise is motivated by the results of Pástor and Veronesi (2003). For high profitability firms, paying dividends is found to decrease the Market-to-Book equity ratio, as funds are taken out of the company.

In addition, we will control the benchmark sample for the ESG score to assess how it affects a company's stock price. In line with the literature discussed in section 2.4, we believe that investors acknowledge the presence of an ESG score positively and are further willing to pay a higher price for this metric. As we want to assess if an ESG score is worth a higher price in excess of the other quality factors, we add an ESG score dummy as an additional control in our cross-sectional quality regressions. This ESG score dummy variable takes on the value of 1 if the company has an ESG score in the current year and 0 otherwise.

Moreover, we will run cross-sectional regressions similar to Asness et al. (2018b) that include all individual quality scores to determine which factor has the largest impact on price when considering all factor scores simultaneously. We do this for both the benchmark scenario and the smaller sample size, which includes the ESG score discussed in 5.1.4 (equation 44).

$$P_t^i = a + b^1\ profitability_t^i + b^2\ growth_t^i + b^3\ safety_t^i + b^4\ ESG_t^i + \epsilon_t^i \tag{44}$$

The inclusion of the calculated z-scores as explanatory variables for quality limits the possibility of outliers due to their ranking characteristics. Moreover, the interpretation of the b^i coefficient is intuitive and straightforward. A one standard deviation increase in any of the Z_t^i quality scores implies a percentage increase in the market-to-book ratio of b^i. If an investor is willing to pay a higher price for a stock, the b^i coefficient should be positive and significant. A negative b^i coefficient implies that a one standard deviation increase in the quality score decreases the market-to-book ratio by b^i %. We will run these regressions for the entire sample period and on a yearly basis. These regressions will give us an overview of whether a quality premium is priced into the market-to-book ratio over several years (Asness et al., 2018b).

The goodness-of-fit test is usually considered the R-squared of a regression, which is the ratio of the explained variation (SSE) of the regression to the total variation (SST). The R-squared can only take values between zero and one. If the explanatory variables are close to zero, they do not have significant explanatory power, and the R^2 of the regression is small (Wooldridge (2013), p.80). However, in most research papers, the adjusted R-squared (equation 45) is usually reported, which has the same characteristics as the R-squared, but with the nice feature that a penalty is introduced for adding additional explanatory variables. This is a good feature since adding an additional independent variable to a model should be reasonable and not done only for increasing the R-squared of a regression. For this reason, we use the adjusted R-squared $\overline{R}$ as a goodness-of-fit measure which consists of the sum of squared residuals (SSR) and the total variation (SST) (Wooldridge (2013), p.202).

$$\overline{R}^2 = 1 - \frac{[SSR/(n-k-1)]}{[SST/(n-1)]} \tag{45}$$

The results of equation 42 for the different factors will determine our composite quality score. If factors are positively related to the stock price, they will be associated with higher quality and therefore be included in the quality score.

5.3 Portfolio construction

The combined quality score resulting from the factor regressions in section 6.1 is used to assign each stock to a quality-sorted portfolio. In contrast to the monthly quality sorting in Asness et al. (2018b), we rebalance our portfolio every year, as we use annual accounting data. Nevertheless, annual rebalancing is quite common in the literature, performed in studies such as Novy-Marx (2013, 2014a) and Hsu et al. (2018).
Our accounting data is available from 1999 onward. Therefore, we base our first company ranking on the calendar year-end 2005. Since all listed companies in Germany are required to publish their financial statements in the first four months of the following year (§325 German Commercial Code[28] and §264d German Commercial Code[29]), it is possible to invest from May 1, 2006 onwards. This approach is consistent with Fama and French (1992) since we match all accounting data in year t-1 and start investing in year t. This results in an investment horizon from May 1, 2006, to December 31, 2021.

We therefore invest twelve consecutive months based on the financial report of year t-1 until the companies publish the next year's report. To invest on a monthly basis as in Asness et al. (2018b), we need to calculate monthly returns based on closing stock prices P_i, by using the standard one-period returns equation $\frac{(P_t - P_{t-1})}{P_{t-1}}$.
Different portfolio sizes are chosen throughout the related literature. Asness et al. (2018b) and Sloan (1996) create ten different portfolios based on the ranked quality score, while Novy-Marx (2013) splits the scores into five portfolios. The most common approach though, as in Novy-Marx (2014a), Hsu et al. (2018), and Kozlov and Petajisto (2013), is to construct a quality portfolio that includes stocks with a top 30% quality rank and a junk portfolio including the stocks with a bottom 30% quality rank.
To cover most standard approaches in the literature, we first split the sample into five quality portfolios. The stocks with the lowest quality z-scores are assigned to portfolio *P1*, and those with the highest z-scores are assigned to portfolio *P5*. All portfolios are equally sized unless the number of observations could not be divided by five, in which case the portfolios with the lower quality stocks contain additional observations. Further, we construct a portfolio consisting of the 30% highest-quality stocks *PQ30* and another portfolio with the 30% lowest-quality stocks *PJ30*. In addition, we consider different long-short portfolios. First, we invest in the highest quality portfolio *P5* and short the lowest quality portfolio *P1*. We call this portfolio Top minus Bottom (TMB).

[28] https://www.gesetze-im-internet.de/hgb/__325.html
[29] https://www.gesetze-im-internet.de/hgb/__264d.html

$$TMB = P5 - P1 \tag{46}$$

Second, we go long in the portfolio *PQ30* and short the portfolio *PJ30*. This portfolio is called *TMB30*. Since all long-short portfolios are self-financing, there is no need to deduct the risk-free rate from these portfolios (Asness et al., 2018b).

$$TMB30 = PQ30 - PJ30 \tag{47}$$

In our initial approach, the portfolio returns are weighted by their market capitalization and recalculated every month to maintain the weights. The market capitalization weights are calculated relative to the total market capitalization of the quality-sorted portfolio. The market capitalization[30] weight of firm i is therefore constructed as in Asness et al. (2018b):

$$\frac{Market\ Capitalization_i}{\sum_i^P Market\ Capitalization} \tag{48}$$

This scenario benefits the larger companies in the sample, as they receive a higher weight due to their high market capitalization. Therefore, we also use an approach of equally weighing the stocks each month. There, smaller stocks receive a larger weight compared to the market value weighting approach discussed above. The weights in both approaches add up to one each month.

Related literature, such as studies done by Novy-Marx (2014a) or Asness et al. (2018a), concludes that size matters. Our sample of 653 companies includes some of the largest companies in Germany by market capitalization, such as *SAP SE, Siemens AG, Bayer AG* and *Mercedes-Benz Group AG*. Regardless of the portfolio they are included in, these companies have the largest investment weights in the value-weighted approach. To address this imbalance, the portfolios are often sorted on size first and only afterward on quality. For non-U.S. markets, there are two typical approaches of size sorting often used in the literature.
Hsu et al. (2018) and Kozlov and Petajisto (2013) include the 10% largest companies by market capitalization into their big firm sample, and the other 90% into the small sample. The big sample of Asness et al. (2018a) and Asness et al. (2018b), on the other hand, contains the 20% largest companies by market capitalization, while the remaining 80% are assigned to the small sample. However, other subdivisions, such as the median often used for the US market, are also conceivable to meet specific market conditions.

[30]Market capitalization and market value will in the following be used as synonyms.

In our benchmark approach we decided to use the 80/20 approach to assign our German companies into a big and a small sample. As a robustness check we use the other size breakpoints mentioned above. After sorting for size, we sort the companies in each sample according to their quality score. This results in a big (small) quality portfolio including the 30% highest-quality stocks and a big (small) junk portfolio, including the 30% lowest-quality stocks. Additional to the long portfolios, we construct long-short strategies. The *BQMJ* strategy buys the 30% highest quality stocks *BQ* and shorts the 30% lowest quality stocks *BJ* within the big sample. In contrast, the *SQMJ* strategy buys the 30% highest quality stocks *SQ* and shorts the 30% lowest quality stocks *SJ* within the small sample. Since we already accounted for the size effect, we only use value-weighted weighting in the big and small quality portfolios.

$$BQMJ = BQ - BJ \tag{49}$$

$$SQMJ = SQ - SJ \tag{50}$$

From these two long-short portfolios the *QMJ* portfolio from Asness et al. (2018b) can be constructed (see equation 51). The *QMJ* factor is calculated by taking a long position in the average return of the two quality portfolios and a short position in the average return of the two junk portfolios.

$$QMJ = 0.5 * (BQ + SQ) - 0.5 * (BJ + SJ) \tag{51}$$

This selection of portfolios allows us to take a wide variety of investment opportunities in quality stocks.

5.4 Performance measures

To compare these portfolios, we need to consider various performance measures. The easiest way of evaluating the performance of a portfolio is to look at returns. As explained in section 3.3 regarding the CAPM, the most intuitive way is to split returns into alpha and beta coefficients. In the Fama-French three-factor model discussed in 3.4 and the Fama-French five-factor model discussed in 3.5, we take additional risk exposures into account, the factor portfolios, and calculate the quality-sorted portfolios' alphas. The CAPM and the Fama-French three-factor model are quite common regression models for portfolio performance evaluation, as shown in Asness et al. (2018b), Novy-Marx (2014a), Novy-Marx (2013) or Kozlov and Petajisto (2013). In Asness et al. (2018b), the five-factor model was also used as a performance measure.

In our regression models, we use the Fama-French European Factors[31] market (MKT), size (SMB), book-to-market (HML), profitability (RMW), and investment (CMA) and adjust these by our risk-free rate.

If we still observe significant positive alphas after taking the risk exposures into account, we can be confident that our quality-sorting process is the base for an investment strategy that delivers significant average returns (Pedersen (2015), p.27-29). However, before we can run these time-series regressions, we must first calculate the excess returns of our portfolios.
The following performance measure are similar to the ones from (Pedersen (2015), p.27-32). The excess return can be calculated by subtracting the risk-free rate r^f, defined in section 4.2, from the portfolio return r^p, where p stands for one of the different portfolios.
A significant positive alpha shows that the investment strategy makes money, and a negative alpha shows the opposite. However, alpha does not take the risk of the excess return into account. For this reason, risk-reward ratios offer better comparability.

One of the most common risk-reward ratios is the Sharpe ratio (SR). The Sharpe ratio (equation 52) measures the return of an investment in relation to the risk of the investment. The numerator contains the expected excess return of a portfolio $r^p - r^f$, while the denominator contains the standard deviation of the excess return. A higher Sharpe ratio, i.e. better risk-adjusted performance of the portfolio, is achieved by a higher expected excess return or a lower volatility of the excess return (Pedersen (2015), p.29).

$$SR = \frac{E(r^p - r^f)}{\sigma(r^p - r^f)} \tag{52}$$

To calculate the Sharpe ratio of each portfolio, we also need to calculate the average arithmetic excess return of these portfolios (ER), where T is the total number of months in the portfolio (equation 53)

$$ER = \frac{(r_1^p + r_2^p + ... + r_T^p)}{T} \tag{53}$$

Since we use monthly stock returns, we annualize the average return and volatility to get annualized Sharpe ratios. The annualized return is obtained by multiplying the arithmetic average excess return by $n = 12$ months.

$$ER^{annual} = ER * 12 \tag{54}$$

[31] The data can be downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Annualized volatility is calculated by multiplying the standard deviation of the excess return by the square root of n. In our case,

$$\sigma^{annual} = \sigma * \sqrt{12} \tag{55}$$

So overall, the annualized Sharpe ratio can be computed as in equation 56 (Pedersen (2015), p.32-34) and is a common way of comparing the performance of investment strategies, as it can be seen in Asness et al. (2018b), Kozlov and Petajisto (2013) or Hsu et al. (2018).

$$SR^{annual} = \frac{ER^{annual}}{\sigma^{annual}} \tag{56}$$

Annualized alphas are calculated similarly by multiplying the monthly alpha with the factor 12. This selection of performance measures allows us to evaluate and compare our quality-sorted portfolios.

6 Results

Having established the theoretical framework in section 3 and explained the methodology in section 5, we can now apply both to our sample. We start by testing if the factors examined in section 2 are associated with a higher stock price. Afterward, the factors related to higher stock prices will be included in our combined quality score, which we will then use to create quality-sorted portfolios in section 6.2.
The following list illustrates our empirical approach:

1. Testing effect of factors on stock prices
2. Checking robustness of our quality definition
3. Quality-sorted portfolios (value-weighted)
4. Quality-sorted portfolios (equal-weighted)
5. Size-sorted quality portfolios 80/20 sample split
6. Size-sorted quality portfolios 90/10 sample split
7. Size-sorted quality portfolios Median sample split
8. Size-sorted quality portfolios Industry specific sample split

The main results of our approach, documented in the list above, will be shown in this chapter, while additional results can be found in the appendix.

6.1 Quality Impact on Prices

Following the methodology derived in section 5.2, we start our analysis by determining if the factors command higher prices in our sample. Using the *z-scores* constructed in section 5.1, we first regress the price on the factors separately and afterward on our combined quality factor given by the quality *Z-score*. As discussed in 5.2, we conduct those cross-sectional regressions for both the benchmark sample and the smaller sample, which includes the ESG score. We start by separately regressing price on the *z-scores* of our quality factors, starting with profitability. The following interpretation of all the z-score coefficients in the regressions is conducted as in Asness et al. (2018b) since they developed the score.

The results of the cross-sectional profitability regression agree with the literature discussed in section 2.1 and our methodology derived in section 3.2. The profitability *z-score* has a positive coefficient every year and for the full sample, which can be seen in tables 23 & 24 in the appendix. Further, all coefficients are significant each year. During the period 2006-2021, a higher profitability score will increase the corresponding stock price. Surprisingly, the profitability coefficient more than halves from 2020 to 2021. The full sample regression is shown below in equation 57.

$$P_t^i = 0.595 + 0.189\ Profitability_t^i + \epsilon_t^i \tag{57}$$

An increase of one standard deviation in the profitability *z-score* leads to a stock price increase of 18.9%. Further, the adjusted R^2 is at 4.7%, meaning that profitability only explains 4.7% of the stock price changes.
The same concept is used to regress the stock price on the *z-score* for growth. The results are very similar to the profitability *z-score*, with all positive and significant coefficients, shown in tables 25 & 26 in the appendix. Equation 58 again presents the full sample output.

$$P_t^i = 0.595 + 0.209\ Growth_t^i + \epsilon_t^i \tag{58}$$

An increase of one standard deviation in the growth *z-score* leads to a 21% increase in the stock price when looking at the full sample. Growth has a slightly bigger impact on stock prices than profitability and a slightly higher explanatory power adjusted R^2 of 5.8%.

The same picture as with profitability and growth can be drawn with the safety factor. Regressing stock prices on the safety *z-score*, entails again positive and significant coefficients, shown in tables 27 & 28 in the appendix. The coefficients are almost always of lower magnitude than the coefficients for profitability and growth examined above. The full sample equation for safety is shown in equation 59 below.

$$P_t^i = 0.595 + 0.131\ Safety_t^i + \epsilon_t^i \tag{59}$$

An increase of one standard deviation of the safety *z-score* increases the stock price by 13%. The adjusted R^2 is only 2.3%, implying that safety explains even fewer stock price variations than the other quality factors.

As discussed in section 2, *Profitability, Growth* & *Safety* are linked to higher prices, which is why our benchmark sample quality factor is similarly to Asness et al. (2018b) created as a *z-score* from these factors.

$$Quality = z(Profitability + Growth + Safety) \tag{60}$$

The regression of the stock price on the combined quality *z-score* is shown in tables 7 and 8.

Table 7: Cross-section regressions Quality Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z quality	0.196***	0.224***	0.211***	0.170***	0.184***	0.221***	0.244***	0.216***
	(0.040)	(0.037)	(0.039)	(0.043)	(0.037)	(0.033)	(0.038)	(0.039)
Cons	0.700***	0.745***	0.534***	0.089**	0.398***	0.538***	0.403***	0.443***
	(0.040)	(0.037)	(0.039)	(0.043)	(0.037)	(0.033)	(0.038)	(0.039)
N	381	407	394	383	393	415	435	420
Adj R^2	0.057	0.080	0.066	0.037	0.056	0.095	0.084	0.066

Note: *p<0.1; **p<0.05; ***p<0.01

The coefficients for the quality *z-score* show similar developments compared to the individual *z-scores* of the benchmark quality factors. The coefficients are especially low around the global financial crisis from 2008 to 2009, implying that quality has a lower impact on stock prices during this period.
We again observe the magnitude of the coefficients to decrease significantly in 2021. Equation 61 shows the full sample impact of quality on stock prices.

$$P_t^i = 0.595 + 0.224\ Quality_t^i + \epsilon_t^i \tag{61}$$

Table 8: Cross-section regressions Quality Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z quality	0.204***	0.190***	0.222***	0.273***	0.298***	0.305***	0.271***	0.169***	0.224***
	(0.040)	(0.043)	(0.042)	(0.043)	(0.043)	(0.045)	(0.051)	(0.053)	(0.011)
Cons	0.627***	0.687***	0.654***	0.807***	0.838***	0.699***	0.534***	0.940***	0.595***
	(0.040)	(0.043)	(0.042)	(0.043)	(0.043)	(0.045)	(0.051)	(0.053)	(0.011)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.058	0.047	0.069	0.098	0.117	0.115	0.072	0.026	0.067

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows yearly quality scores. For each year, stocks are ranked in ascending order based on their accounting values within the quality scores. The coefficients shown in the table are the values from a regression of logarithmic Market-to-Book values for a company on the combined quality z-scores. The sample period runs from 2006 to 2021, but only the years 2014 to 2021 as well as the total sample coefficients are shown in this table. Years 2006 to 2013 are shown in table 7 above.

The regression 61 yields a similar result as in the quality regressions conducted by Asness et al. (2018b). The magnitude of the combined *z-score* is larger compared to the individual *z-scores*. An increase of one standard deviation in the quality *z-score* leads to a stock price increase of 22%. The adjusted R^2 is slightly larger than for the individual *z-scores*, but even now, only 6.7% of the stock price changes are explained by the quality *z-score*. Nonetheless, these results show that higher quality is rewarded with a higher stock price. Hence, the relationship between the quality and the Market-to-Book ratio, set out to prove in section 3.2, holds.

We have so far been able to show that our benchmark sample quality score is linked to higher stock prices. Now, the ESG factor discussed in section 2.4 is examined for its possible quality characteristics. In our small sample approach, which only includes firms with an ESG score in a given year, we regress stock prices on the ESG *z-score* in the same matter as in our benchmark model.

The results are surprising and contrary to the related literature from section 2.4. The ESG *z-score* coefficient is negative, which implies that a higher ESG score leads to a lower stock price. This result raises doubt about the classification of ESG as a quality metric. While the *z-scores* are not constantly significant throughout the years, the coefficient of full sample performance is significant to a 1% level. Equation 62 below shows the regression of the stock price on the ESG score in our small sample. The full results can be seen in tables 29 and 30 in the appendix.

$$P_t^i = 0.775 - 0.105\ ESG_t^i + \epsilon_t^i \tag{62}$$

An increase of one standard deviation in the ESG *z-score* will decrease the stock price by 10.5%. The adjusted R^2 is again very small with 1.6 %, so the ESG score captures only minimal stock price variation. Because the ESG score has a negative effect on stock prices, it is not found to be a quality factor in our sample. Therefore, we will not create a second quality score for a smaller sample size that includes ESG, but rather continue with our quality score definition from the benchmark sample.

A negative ESG score impact on stock prices is surprising, given the findings of related literature in section 2.4. Therefore we want to examine the impact of an ESG score in a second way. By including an ESG score dummy in the benchmark sample, we check if having an ESG score positively impacts stock prices. The ESG score dummy indeed has a positive significant coefficient. The full sample results are shown in the equation 63, and additional result are shown in tables 31 & 32.

$$P_t^i = 0.558 + 0.218\ Quality_t^i + 0.183\ ESG\ Dummy_t^i + \epsilon_t^i \tag{63}$$

As the ESG score either takes on the values 0 or 1, the interpretation is different from before. If the company has an ESG score in a given year, meaning the dummy variable has the value of 1, the stock price will increase by 18.3%. Therefore having an ESG score seems to be a sign of quality, connected to a higher stock price. By controlling for quality in equation 63, the ESG score impact is in excess of the quality score. While the ESG approaches cannot be compared straight up, it is interesting that the ESG factor's impact is now positive, opposite to before. Compared to equation 61, the quality coefficient has decreased only marginally from 22.4% to 21.8%. The small change implies that there is little correlation between the quality factors of the benchmark model and the ESG dummy factor, and adding the dummy to the benchmark model leads to more explained variations in stock prices.

Even though we have already created our combined quality score, we are nonetheless interested in the magnitude and statistical significance of the variables when included together in regressions of the stock price. Table 9 shows the results of the multiple regressions of our benchmark factor model, the benchmark factor model including the ESG score dummy, as well as the small sample model including the ESG factor.

We start with the benchmark model shown below in regression 64.

$$P_t^i = 0.595 + 0.094\ Profitability_t^i + 0.151\ Growth_t^i + 0.039\ Safety_t^i + \epsilon_t^i \tag{64}$$

Table 9: Cross-section regressions individual quality factors

	log firm value		
	Full sample	Full sample + ESG	Small sample + ESG
z profitability	0.094***	0.093***	0.165***
	(0.014)	(0.013)	(0.028)
z growth	0.151***	0.150***	0.184***
	(0.012)	(0.012)	(0.026)
z safety	0.039***	0.032***	0.078***
	(0.012)	(0.012)	(0.023)
DV ESG		0.193***	
		(0.026)	
z ESG			−0.074***
			(0.020)
Cons	0.595***	0.556***	0.775***
	(0.011)	(0.012)	(0.020)
N	6,129	6,129	1,251
Adj R^2	0.072	0.080	0.213

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows average quality scores. For each year, stocks are ranked in ascending order based on their accounting values within the quality scores. The coefficients shown in the table are the values from a regression of logarithmic Market-to-Book values for a company on the separate factor z-scores for profitability, growth, safety, ESG and an ESG dummy variable. The sample period runs from 2006 to 2021, but only the total sample coefficients are shown in this table. Both the full sample and the smaller sample including the ESG factor are shown

The three *z-scores* stay significant when used in a multiple regression setting, which is encouraging. This result supports our approach of deriving the quality *z-score* as a sum of the individual quality factor *z-scores*.

All three coefficients are positive but of lower magnitude than their respective single regressions. This is not surprising, considering that more of the stock price variation is explained by the other included quality factors. The growth coefficient is the largest among the three-factor model, so as before, growth has the largest impact on stock prices. Further, the adjusted R^2 of 7.2% is slightly higher than in the previous regressions due to the increased number of control variables. The explained variation is still very low, so similar to Asness et al. (2018b) we include additional controls.

Next, we include the ESG score dummy discussed above into equation 64. This leads to equation 65 shown below.

$$\begin{aligned} P_t^i = 0.556 + 0.093\ Profitability_t^i + 0.150\ Growth_t^i + 0.032\ Safety_t^i \\ +0.193\ ESG\ Dummy_t^i + \epsilon_t^i \end{aligned} \tag{65}$$

The magnitude and sign of the coefficients are almost equal to equation 64, and all coefficients are highly significant. The ESG factor dummy coefficient is now slightly higher compared to equation 63, confirming that even when controlling for the separate factors, having an ESG score still has a significant positive impact on stock prices. The ESG dummy factor indeed explains prices in excess of *quality.*
The interpretation of this result omits two essential aspects. First, not having an ESG score should not necessarily be punished. Second, the dummy misses the differences in scale between the values. Therefore, having an ESG score should not automatically be associated with a positive interpretation.

Lastly, we circle back to the small sample analysis including the ESG factor *z-score* discussed in equation 62. The regression including the three benchmark factors and the ESG score is shown below in equation 66.

$$P_t^i = 0.775 + 0.165\ Profitability_t^i + 0.184\ Growth_t^i + 0.078\ Safety_t^i - 0.074\ ESG_t^i + \epsilon_t^i \quad (66)$$

We can see that the coefficients for the *z-scores* of profitability, growth and safety have positive effects on the stock price in the small sample. In contrast, the ESG *z-score* coefficient is still negative, as already discussed for equation 62.

The positive impact of the quality score on stock prices also holds for the small sample, as shown below in 67. This underlines, that our quality definition works independently of the sample size.

$$P_t^i = 0.775 + 0.360\ Quality_t^i + \epsilon_t^i \quad (67)$$

Full results for these regressions can be seen in the appendix in tables 33 & 34.
In conclusion, our quality score moving forward will consist of the factors *Profitability, Growth* & *Safety*, that were also associated with quality in Asness et al. (2018b). As shown, this quality score commands a 22% increase in stock prices. This is in the same sphere as Asness et al. (2018b), who find a 17% stock price increase for their global sample. An additional quality score including the ESG factor will not be created, as the ESG score negatively affects stock prices. We will continue our analysis with the benchmark sample approach.

6.1.1 Robustness of Quality regressions

The quality score defined in the last section has shown relatively low explanatory power in tables 7 & 8. We therefore test for the robustness of the quality score by including additional control variables that might explain additional variation in stock prices.

Equation 68 controls for a firm's size while equation 69 includes the dividend dummy in the quality score regression. Equation 70 uses both controls next to the quality score, and equation 71 additionally adds the ESG score dummy.

$$P_t^i = 0.595 + 0.182\ Quality_t^i + 0.152\ Size_t^i\ + \epsilon_t^i \tag{68}$$

$$P_t^i = 0.648 + 0.243\ Quality_t^i - 0.116\ Dividend\ Dummy_t^i\ + \epsilon_t^i \tag{69}$$

$$P_t^i = 0.732 + 0.216\ Quality_t^i + 0.213\ Size_t^i\ - 0.298\ Dividend\ Dummy_t^i + \epsilon_t^i \tag{70}$$

$$\begin{aligned} P_t^i = 0.740 + 0.214\ Quality_t^i + 0.223\ Size_t^i\ - 0.296\ Dividend\ Dummy_t^i \\ -0.042\ ESG\ Dummy_t^i + \epsilon_t^i \end{aligned} \tag{71}$$

Controlling for the different variables yields some valuable insights. As in Asness et al. (2018b), bigger companies have higher stock prices when controlling for quality, with stock prices increasing by 15.2% when increasing the standard deviation of size by 1, seen in equation 68. The coefficient jumps to 21% when also controlling for dividend-paying firms, seen in equation 70. Large firms are more expensive than small firms when the level of quality is the same.

Further, dividend paying firms have 11% lower stock prices when controlling for quality, as in equation 69. The result confirms that dividend-paying firms have lower Market-to-Book ratios than non-dividend-paying firms, even when the quality is the same, which is not surprising since stock prices usually decline by the dividend after the payout. The quality factor coefficient increases when controlling for dividends (DV Div), which is consistent with dividend-paying firms being more profitable than non-dividend-paying firms (Hou & Van Dijk, 2019). If we additionally control for size, dividend-paying firms have 30% lower stock prices, again seen in equation 70.

Lastly, we also control for the ESG dummy, for which we found significant returns in excess of the quality score in equation 65. The impact of the ESG dummy on stock prices is now insignificant. The returns to firms with an ESG score seem to be explained by either size or the dividend-payer dummy. Looking back at figure 5, we see that the 10 companies with the highest ESG scores, who had an ESG score over the whole sample are also 10 of the largest German companies by market capitalization. The stock price impact of ESG firms is therefore likely explained by the firms' size.

Table 10: Cross-section regressions Quality - control for size, dividends and ESG Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z quality	0.168***	0.213***	0.193***	0.161***	0.206***	0.225***	0.238***	0.200***
	(0.042)	(0.037)	(0.040)	(0.043)	(0.040)	(0.036)	(0.041)	(0.041)
z size	0.287***	0.312***	0.340***	0.309***	0.209***	0.154***	0.203***	0.197***
	(0.052)	(0.046)	(0.050)	(0.055)	(0.049)	(0.044)	(0.052)	(0.054)
DV Div	−0.449***	−0.408***	−0.440***	−0.388***	−0.297***	−0.262***	−0.263***	−0.253***
	(0.090)	(0.082)	(0.087)	(0.096)	(0.088)	(0.076)	(0.091)	(0.089)
DV ESG	−0.112	−0.213*	−0.257*	−0.182	0.047	0.017	−0.058	0.026
	(0.138)	(0.129)	(0.133)	(0.145)	(0.130)	(0.115)	(0.132)	(0.134)
Cons	0.906***	0.951***	0.783***	0.290***	0.510***	0.653***	0.527***	0.552***
	(0.056)	(0.052)	(0.059)	(0.061)	(0.052)	(0.049)	(0.057)	(0.058)
N	381	407	394	383	393	415	435	420
Adj R^2	0.148	0.186	0.175	0.121	0.118	0.135	0.119	0.107

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Cross-section regressions Quality - control for size, dividends and ESG Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z quality	0.190***	0.153***	0.201***	0.271***	0.307***	0.307***	0.245***	0.188***	0.214***
	(0.042)	(0.046)	(0.045)	(0.047)	(0.046)	(0.048)	(0.053)	(0.055)	(0.011)
z size	0.230***	0.253***	0.211***	0.207***	0.210***	0.228***	0.310***	0.408***	0.223***
	(0.055)	(0.061)	(0.061)	(0.063)	(0.065)	(0.071)	(0.077)	(0.070)	(0.014)
DV Div	−0.237**	−0.234**	−0.217**	−0.325***	−0.405***	−0.339***	−0.217*	−0.395***	−0.296***
	(0.094)	(0.100)	(0.099)	(0.101)	(0.097)	(0.103)	(0.114)	(0.121)	(0.024)
DV ESG	−0.026	−0.082	−0.152	−0.066	−0.087	−0.160	−0.438***	−0.413***	−0.042
	(0.138)	(0.145)	(0.142)	(0.147)	(0.143)	(0.140)	(0.148)	(0.135)	(0.032)
Cons	0.741***	0.817***	0.789***	0.989***	1.084***	0.930***	0.784***	1.343***	0.740***
	(0.061)	(0.069)	(0.068)	(0.072)	(0.076)	(0.083)	(0.088)	(0.101)	(0.016)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.105	0.095	0.096	0.134	0.167	0.150	0.107	0.116	0.117

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows the cross-sectional quality regressions of the Market-to-Book ratio as a logarithm on the z-scores of the combined quality score and a size factor. The size factor is the market capitalization of a firm and is created as a z-score to be consistent with the other quality factors. Market-to-Book ratio is further regressed on a dividend-payer dummy variable and an ESG score dummy variable. The dividend-payer dummy indicates, if a firm payed out dividends within the prior year. The ESG dummy indicated, if a firm has an ESG score within the same years. The sample period runs from 2006 to 2021. This table only shows the years 2014 to 2021, for the results of the years 2006 to 2013, refer to table 10 above.

Overall, small dividend-paying firms with low quality are found to have the lowest stock prices.

Detailed results for the control regressions can be found in the tables 10 & 11. Further results are shown in the appendix in tables 35 & 36 when controlling for size, 37 & 38 when controlling only for dividends, and 39 & 40 when controlling for both size and dividends. By including various controls in the cross-sectional quality regressions, the explanatory power increased from 6% to 11%, still leaving a lot of stock price variations unexplained. The quality factor varies in magnitude depending on the specification, reaching the highest coefficient of 24.3% when controlling for dividend-paying firms, consistent with the theory (Pástor & Veronesi, 2003). Still, as the changes in the coefficient are not large, the quality score seems robust to the inclusion of controls, especially because the quality score continues to show high statistical significance.

6.2 Investment portfolios

As our quality score is not only related to higher stock prices but also robust to the inclusion of different specifications, we use this quality *z-score* of equation 60 for the creation of quality-sorted factor portfolios defined in section 5.3.

6.2.1 Quality-sorted portfolios - Value-weighted

Our initial portfolios are sorted only by quality as described in section 5.3. Within these portfolios, we use market value weights that are rebalanced monthly to maintain the weights. Table 12 and the performance measure tables show both monthly and annual performance measures. As our CAPM and Fama-French regressions use monthly returns, the corresponding performance measures and factor betas are also delivered monthly. The same is true for p-values, on which basis statistical significance is assessed. However, in most related literature on factor investing, performance measures are usually annualized to provide better comparability across samples and years. In order to not violate the statistical properties within our regressions but also be in line with factor investing procedure, we report both monthly and annualized performance measures. The CAPM and Fama-French tables throughout our thesis show monthly alphas and factor betas.
We are set out to show that investing in higher quality can increase returns. In line with factor investing theory such as in Asness et al. (2018b), we expect the excess returns and Sharpe ratios to increase in quality. The lowest-quality portfolio *P1* should have the lowest risk-adjusted return, and the highest-quality portfolio *P5* the highest risk-adjusted return. The CAPM and Fama-French alphas, which are the excess portfolio returns not explained by the exposure of the additional factors, are expected to increase similarly for higher-quality portfolios.

However, these are not quite the results we observe in table 12. The lowest-quality portfolio *P1* has an annual expected excess returns of 6.3%, which is higher than the expected excess

Table 12: Performance measures value weighted portfolios

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
monthly									
ER	0.005	0.001	0.003	0.006	0.006	0.003	0.007*	0.001	0.004
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)
CAPM α	0.001	−0.003	−0.001	0.002	0.002	−0.002	0.003	0.001	0.005*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Fama 3 α	0.0002	−0.003	−0.001	0.002	0.001	−0.001	0.002	0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Fama 5 α	0.001	−0.005	−0.002	0.001	0.000	−0.002	0.001	−0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
annual									
ER^{annual}	0.063	0.013	0.033	0.072	0.069	0.035	0.085	0.007	0.049
SR^{annual}	0.279	0.068	0.175	0.394	0.400	0.164	0.473	0.046	0.374
CAPM α	0.012	−0.036	−0.012	0.024	0.024	−0.024	0.036	0.012	0.06
Fama 3 α	0.0024	−0.036	−0.012	0.024	0.012	−0.012	0.024	0.012	0.036
Fama 5 α	0.012	−0.06	−0.024	0.012	0.000	−0.024	0.012	−0.012	0.036

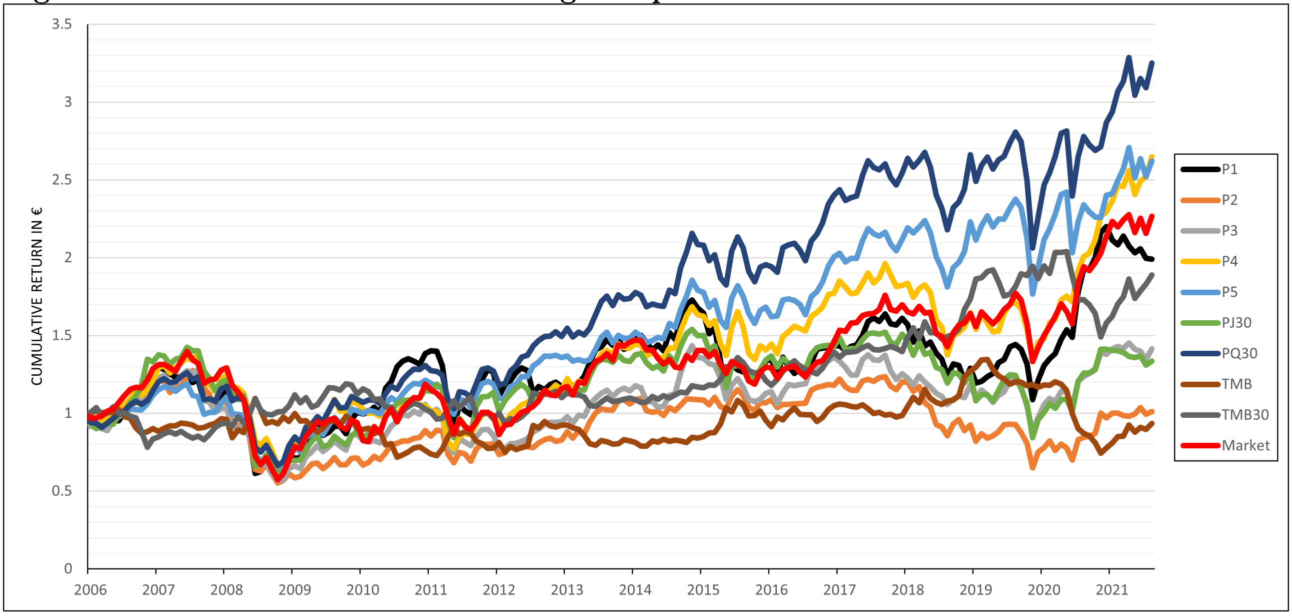
Note: *p<0.1; **p<0.05; ***p<0.01

This table reports monthly and annual performance measures for value-weighted quality portfolios. The stocks are assigned to the quality portfolios based on the quality z-scores. Portfolios P1-P5 show are ascending in quality, while PJ30 and PQ30 show the stocks with the 30% lowest quality and the 30% highest quality. The portfolio TMB is the portfolio long P5 and short P1, while TMB30 is long PQ30 and short PJ30. The stocks are assigned to the portfolios in the beginning of May each year. The portfolios are then invested in for one year. The portfolios returns are weighted with their market capitalization as a fraction of the portfolio's total market capitalization. The performance measures include expected returns, alphas for CAPM, Fama-French three-factor and Fama-French five-factor models both on a monthly as well as annual basis. Additionally, annualized Sharpe ratios are reported. The alphas are the intercept of the time-series regressions of monthly returns of the portfolios. A similar approach is followed for the other Performance measures tables in this thesis

returns of *P2* & *P3*, but those excess returns are not significant on a monthly basis. The only portfolio with significant expected monthly excess returns is portfolio *PQ30*. The portfolio has corresponding expected annual excess returns of 8.5% and an annual Sharpe ratio of 0.47. The Sharpe Ratios gradually increase from *P2* to *P5*. The alphas of the portfolios are not significant though. Therefore, the portfolios do not deliver significant returns in excess of the returns explained by other factors.

Our long-short strategy *TMB* has a very small Sharpe ratio and insignificant monthly alphas. Not a surprising result, given that the lowest-quality and highest-quality portfolios both deliver relatively similar risk-adjusted returns. The other long-short strategy *TMB30* has an annual Sharpe ratio of 0.37 and a significant monthly CAPM alpha of 6%, so it performs significantly better. The monthly Fama-French alphas for *TMB30* are insignificant though, so the difference in expected excess return to long-short strategy *TMB* is explained by the other factors included. Figure 6 shows the development of cumulative returns of the different portfolios and

Figure 6: Cumulative return value weighted portfolios



the market. The graph demonstrates that the high-quality portfolio *PQ30* outperforms the other portfolios and strategies. An investment of 1€ in May 2006 would yield 3.25€ at the end of 2021. Further, *PQ30* and the high-quality strategies *P5* and *P4* outperform an investment in the market.

None of the portfolios or the strategies would have lost money over that period, even though the long-short strategy *TMB* would have achieved a return of only 4 cents. One can observe the different characteristics of the portfolios and strategies when focusing on both the global financial crisis in 2008 and the Covid-19 lockdown in early 2020. We see a heavy drop in the cumulative returns for the long-only portfolios and the market during both crises, while the long-short strategies show almost unchanged cumulative returns. Long-short strategies can absorb the losses of the long-portfolios with gains in the short-portfolios, leading to this neutrality to market volatility.

The portfolios vary quite substantially in their exposure to the market. While the portfolios with higher expected excess returns discussed above also have higher market betas, the portfolios with low expected excess returns *P2* and *P3* also show small betas.

Equation 72 shows the monthly expected excess returns of *PQ30* as a function of the Fama-French three-factor model in table 13.

$$r^e_{PQ30} = 0.002 + 0.858\, r^e_{MKT} - 0.163\, r_{SMB} - 0.361\, r_{HML} + \epsilon_i \tag{72}$$

Table 13: Fama-French 3 factor model - value weights

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
MKT	0.870***	0.763***	0.755***	0.826***	0.824***	0.863***	0.858***	−0.046	−0.006
	(0.066)	(0.057)	(0.054)	(0.048)	(0.045)	(0.060)	(0.044)	(0.064)	(0.055)
SMB	0.338*	−0.083	−0.212	−0.228*	−0.104	0.050	−0.163	−0.442***	−0.214
	(0.173)	(0.148)	(0.141)	(0.127)	(0.118)	(0.156)	(0.115)	(0.167)	(0.145)
HML	0.022	0.136	0.068	−0.205**	−0.373***	0.103	−0.361***	−0.394***	−0.464***
	(0.139)	(0.119)	(0.113)	(0.102)	(0.095)	(0.125)	(0.093)	(0.134)	(0.117)
α	0.0002	−0.003	−0.001	0.002	0.001	−0.001	0.002	0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
N	188	188	188	188	188	188	188	188	188
Adj R^2	0.560	0.581	0.590	0.646	0.662	0.611	0.691	0.094	0.100

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows monthly Fama-French three-factor model regressions. These are time-series regressions of quality-sorted portfolio returns on the Fama-French factors. The portfolios returns are weighted with their market capitalization as a fraction of the portfolio's total market capitalization. The alpha is the intercept of the time-series regression. The explanatory variables are the returns of the Market (MKT), Size (SMB) and Value (HML) factor portfolios. The sample period is from 2006 to 2021. A similar approach is followed for the other Fama-French three factor model tables in this thesis.

As explained in section 3.4, the Fama-French three-factor model includes a Size and a Value factor. When looking at the size factor, we see significant exposures of *P1, P4* and the long-short strategy *TMB*. *P1* has a positive size beta, implying that within the lowest quality portfolio, the small stocks show a positive covariance with the size factor. Interestingly *P4* has a negative size beta, indicating that big companies show a positive covariance with the SMB factor. This holds for the long-short strategy *TMB*, which also has a significant negative coefficient. The second factor introduced by the Fama-French three-factor model is the value (HML) factor. It has negative significant betas for the high-quality portfolios. This result confirms that the general assessment of a negative correlation between the value factor and high-quality holds (Novy-Marx, 2014a).

When adopting the Fama-French five-factor framework, we additionally control for a profitability and an investment factor. This changes the portfolio exposure to the value factor. Instead of the negative significant exposures of high-quality portfolios to the value factor, now the portfolios *P5*& *PQ30* have significant positive profitability and insignificant value betas. This confirms at least partially one of the main takeaways of Fama and French (2015). When including the Profitability (RMW) and the Investment (CMA) factor, the Value factor is redundant. The Fama-French five-factor model is shown in the appendix in table 42.

By controlling for more factors than the market, all monthly alphas are now insignificant.

Therefore, the value-weighted quality-sorted portfolios do not explain returns in excess of the market or the other Fama-French factors. Quality portfolios show higher risk-adjusted returns than junk portfolios, but the corresponding expected monthly excess returns are not significant, so the difference in performance is explained by the returns to other Fama-French factors. Our strategies going long high quality and shorting low quality are not delivering significant monthly alphas either, implying that the returns of these strategies are explained by additional factors. More detailed results on the CAPM model can again be found in the appendix in table 41.

6.2.2 Quality sorted portfolios - Equally-weighted

The weighting of investments within the value-weighted portfolios can lead to portfolio returns that are dominated by a few companies with very high market capitalization. This is the case when the size discrepancy within the sample is large. To compensate for the uneven size distribution, we change the weights in the portfolios.
In this approach we use equally-weighted portfolios as described in section 5.3, which increases the investment weight into small companies significantly within each portfolio.

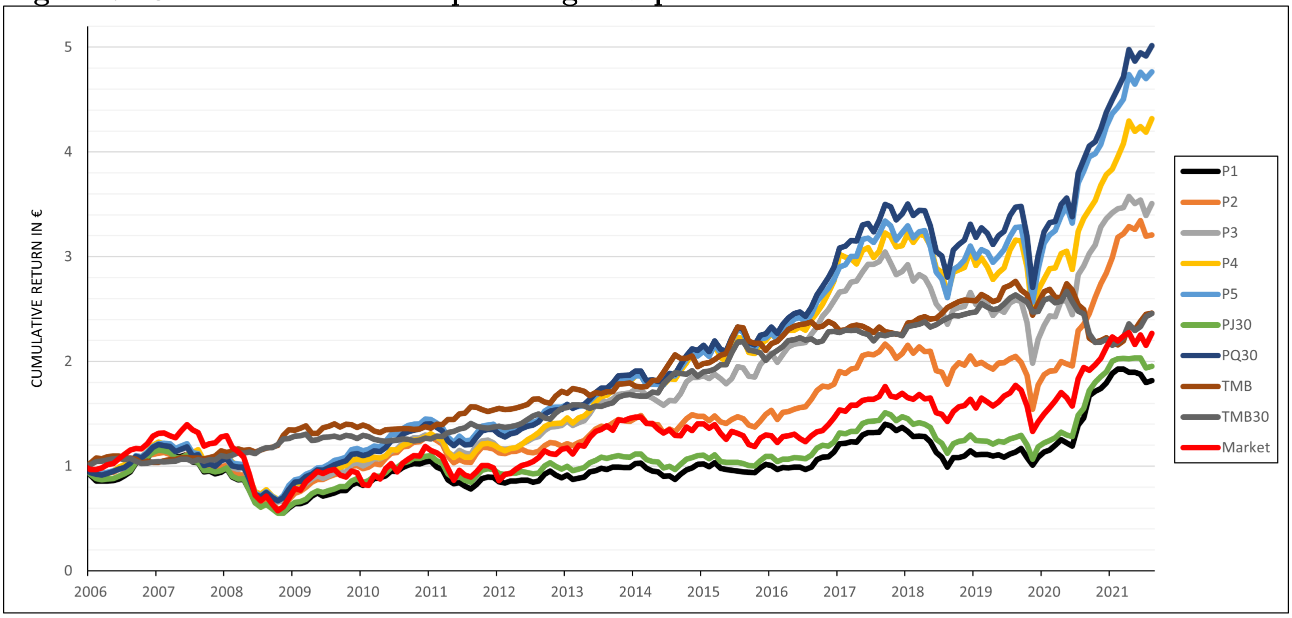
Table 14: Performance measures equal weighted portfolios

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
monthly									
ER	0.004	0.007**	0.007**	0.008***	0.009***	0.004	0.009***	0.005***	0.005***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
CAPM α	0.0004	0.003	0.004**	0.005***	0.005***	0.001	0.006***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Fama 3 α	−0.0004	0.002	0.003**	0.004**	0.004**	0.000	0.004***	0.004**	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Fama 5 α	0.001	0.002	0.003	0.003	0.004**	0.000	0.004**	0.003*	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
annual									
ER^{annual}	0.042	0.079	0.084	0.097	0.103	0.047	0.106	0.061	0.059
SR^{annual}	0.280	0.518	0.583	0.672	0.717	0.314	0.748	0.729	0.882
CAPM α	0.0048	0.036	0.048	0.06	0.06	0.012	0.072	0.06	0.06
Fama 3 α	−0.0048	0.024	0.036	0.048	0.048	0.000	0.048	0.048	0.048
Fama 5 α	0.012	0.024	0.036	0.036	0.048	0.000	0.048	0.036	0.036

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14 shows that the developments of excess returns and Sharpe ratios have changed. Both gradually increase in quality, where *P1* has the lowest, and *P5* has the highest annual Sharpe ratio, with 0.28 respectively 0.71. Higher quality portfolios are now linked to higher expected returns, in line with our expectations. Apart from the two low-quality portfolios *P1* and *PJ30*, the monthly expected excess returns for all portfolios and strategies are significant. Additionally, both long-short strategies show high risk-adjusted returns, with *TMB30* achieving an annual Sharpe ratio of 0.88. The low-quality portfolios do not show significant monthly CAPM alphas, and the inclusion of the Fama-French factors leaves only *P5*, *PQ30* and both long-short strategies *TMB* & *TMB30* with significant monthly alphas. As the investment within the portfolios is equally split between companies, a higher degree of diversification is achieved than in the value-weighted portfolios, where the investment mostly targets big firms. This diversification could explain the higher expected excess returns and significant monthly alphas.

Figure 7: Cumulative return equal weighted portfolios



As before, we also show the development of cumulative returns for the equally-weighted quality portfolios here in figure 7. Compared to the value-weighted quality portfolios, we now see somewhat of a quality hierarchy. The portfolios with the highest quality, *PQ30* and then *P5* clearly show the highest cumulative returns, followed in decreasing quality by the other portfolios. A 1€ investment into *PQ30* in May of 2006 is worth 5€ in 2021 and is of only a slightly lower value for *P5*.

The cumulative return portfolio graphs are now much smoother, being not as volatile compared to value-weights. In the value-weighted approach, the amount invested into stocks within the portfolios is rebalanced each year. In contrast, the stock holdings in the equally-weighted portfolios are basically constant.

Compared to the value-weighted quality portfolios, we also see more evidence for an impact of quality on the expected excess returns in the equally-weighted portfolios, mainly because the high-quality portfolios are able to generate returns in excess of the model factors. Further, the performance of both long-short strategies *TMB* & *TMB30* are worth pointing out. An investment into these strategies now provides expected excess returns, even if they are small.

Table 15: Fama-French 3 factor model - equal weights

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
MKT	0.569***	0.625***	0.589***	0.630***	0.662***	0.581***	0.647***	0.093**	0.066**
	(0.042)	(0.037)	(0.034)	(0.036)	(0.034)	(0.037)	(0.033)	(0.036)	(0.029)
SMB	0.609***	0.583***	0.455***	0.447***	0.453***	0.624***	0.473***	−0.155	−0.152**
	(0.110)	(0.096)	(0.089)	(0.093)	(0.088)	(0.097)	(0.087)	(0.094)	(0.075)
HML	0.019	0.043	0.079	−0.117	−0.221***	0.073	−0.194***	−0.240***	−0.267***
	(0.088)	(0.078)	(0.072)	(0.075)	(0.071)	(0.078)	(0.070)	(0.076)	(0.060)
α	−0.0004	0.002	0.003**	0.004**	0.004**	0.00002	0.004***	0.004**	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
N	188	188	188	188	188	188	188	188	188
Adj R^2	0.606	0.705	0.711	0.690	0.723	0.683	0.724	0.053	0.098

Note: *p<0.1; **p<0.05; ***p<0.01

Equation 73 again shows the expected excess returns of *PQ30* as a function of the Fama-French three-factor model.

$$r^e_{PQ30} = 0.004 + 0.647\, r^e_{MKT} + 0.473\, r_{SMB} - 0.194\, r_{HML} + \epsilon_i \tag{73}$$

The exposure to the market portfolio is now significantly lower compared to the value-weighted approach in table 13. An equally-weighted approach does not follow the market in a similar fashion to the value-weighted approach, as the investment in every firm is the same within a portfolio. In contrast, the value-weighted portfolios follow the market by construction. Therefore, small firms have a much higher weight in the equally-weighted portfolios than their actual market capitalization.

The most obvious change compared to the value-weighted Fama-French three-factor model in table 13 is the size beta. All long-only portfolios have a highly significant positive size coefficient, with the magnitude of the coefficient decreasing in quality. As the portfolios invest equally in all firms, the portfolios have much more exposure to the size factor than before. Portfolio *P1*, for example, has a size beta of 0.609, so the portfolio returns are 61% explained by the returns of the size factor.

The value factor shows similarities to the value-weighted approach, as the both *TMB* and *TMB30* show significant negative betas. Going long high quality and short low quality in our sample is correlated negatively with the returns to the value factor. The inclusion of profitability and investment factors changes the value factor similar to the value-weighted portfolios, where the value factor again becomes redundant in the quality portfolios.

High-quality portfolios show higher expected significant returns within the equally-weighted portfolios, but it is not a realistic approach. The small companies in the sample have low market capitalizations and therefore, only a limited number of shares outstanding. It would be almost impossible to invest an equal share of the portfolio value in each company, as there would have to be continuous rebalancing. Nevertheless, the equally-weighted quality portfolios showed high positive size betas, implying that the size factor explains large variations in portfolio returns. As a result, we introduce conditional sorting in the next section, first by size and then by quality. More detailed results for the equally-weighted can again be seen in the appendix in tables 43 & 44.

6.2.3 Size-sorted Quality portfolios

In section 6.2.2, we found that strategies going long high quality and short low quality can produce significant monthly alphas and returns not explained by other factors. Further, the quality-sorted portfolios showed high size betas, indicating that a size effect is present in our sample.

To control for both quality and size, our sample is first sorted on size and afterward on quality. At first, the sample will be split into a big sample, which includes the 20% biggest companies by market capitalization, and a small sample, including the other 80% of companies consistent with Asness et al. (2018b). Afterward, within both samples, we create a high-quality portfolio consisting of the 30% highest-quality stocks and a low-quality portfolio consisting of 30% lowest-quality stocks. Lastly, the Quality-minus-Junk portfolio from Asness et al. (2018b) is created. In contrast to the previous approaches, the following investment strategies only consider value weights within portfolios.

Table 16 shows the performance of the size and quality-sorted portfolios. Both expected excess returns and the Sharpe ratios are increasing in quality, implying that the quality portfolios *SQ* & *BQ* outperform the junk portfolios *SJ* & *BJ*. The *SQ* portfolio is the only long portfolio displaying significant expected monthly excess returns, with an annual Sharpe ratio of 0.66 and expected annual excess returns of 10.6%.

Table 16: Performance measures size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
monthly							
ER	0.003	0.009***	0.006***	0.002	0.006	0.003	0.005**
	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)
CAPM α	−0.001	0.005**	0.006***	−0.002	0.002	0.004	0.005***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Fama 3 α	−0.001	0.004*	0.005***	−0.002	0.001	0.002	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Fama 5 α	−0.002	0.003	0.005***	−0.003	−0.0003	0.003	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
annual							
ER^{annual}	0.039	0.106	0.067	0.026	0.068	0.042	0.055
SR^{annual}	0.217	0.662	0.755	0.126	0.375	0.335	0.636
CAPM α	−0.012	0.06	0.072	−0.024	0.024	0.048	0.06
Fama 3 α	−0.012	0.048	0.06	−0.024	0.012	0.024	0.048
Fama 5 α	−0.024	0.036	0.06	−0.036	−0.0036	0.036	0.048

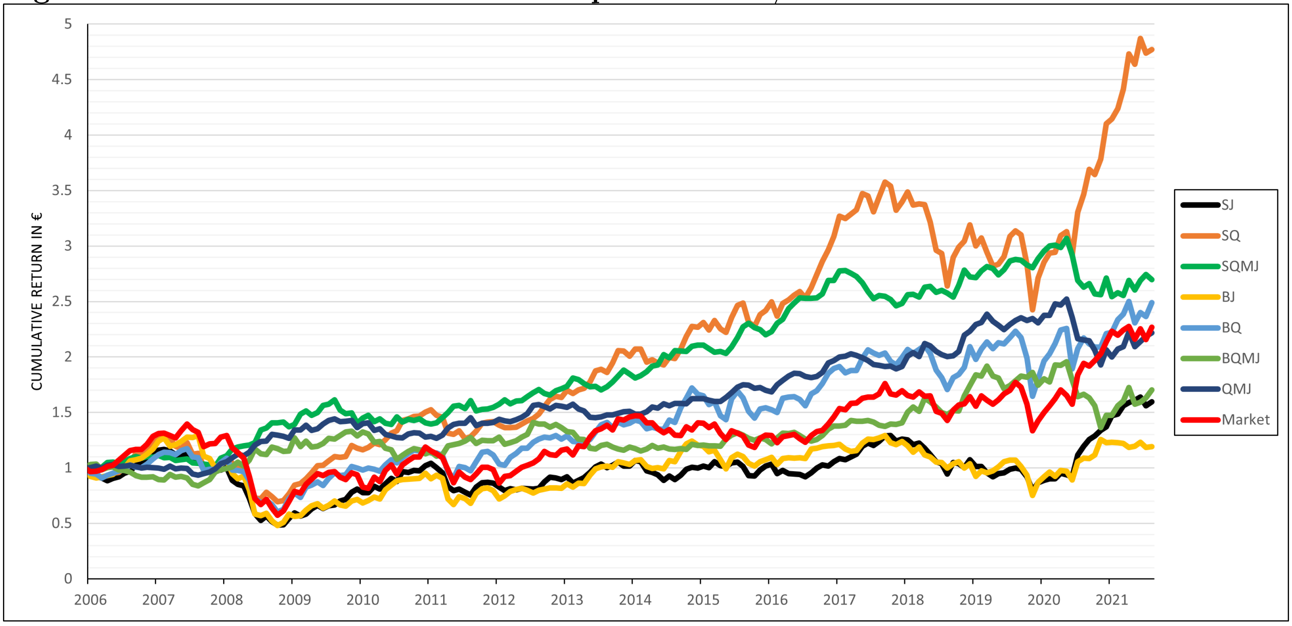
Note: *p<0.1; **p<0.05; ***p<0.01

This table reports monthly and annual performance measures for value-weighted quality portfolios. The stocks are assigned to the quality portfolios conditionally sorted on size and quality scores. SJ is the small junk portfolio, SQ is the small quality portfolio, BJ is the big junk portfolio, BQ is the big quality portfolio, SQMJ is the small quality minus junk portfolio, BQMJ is the big quality minus junk portfolio, and QMJ is the average of SQMJ and BQMJ, the quality minus junk portfolio. The stocks are assigned to the portfolios in the beginning of May each year. The portfolios are then invested in for one year. The performance measures include expected excess returns, alphas for CAPM, Fama-French three-factor and Fama-French five-factor models both on a monthly as well as annual basis. Additionally, annualized Sharpe ratios are reported. The alphas are the intercept of the time-series regressions of monthly excess returns of the portfolios. A similar approach is followed for the other Performance measures tables sorted on size in this thesis

SQ is further the only long portfolio showing a significant monthly CAPM alpha. With 6%, the magnitude of the annual CAPM is in line with the excess returns and Sharpe ratio observations, meaning it outperforms the small junk portfolio *SJ*. The junk portfolios have negative and insignificant monthly alphas, consistent with both portfolios' low, insignificant expected excess returns. Including the Fama-French factors leads to a decrease in magnitude in the alphas for *SQ*, and the monthly alpha loses the significance in the five-factor model. Both the long-short strategy for small portfolios *SQMJ* as well as the *QMJ* portfolio show significant expected monthly excess returns. Further, both have high Sharpe ratios and significant monthly alphas. The annualized market return over the same period is 6.35%, resulting in an annualized Sharpe ratio of 0.334. Looking at the Sharpe ratios of *SQ*, *SQMJ* and *QMJ*, it is clear that the quality portfolios outperform the market proxy.

Figure 8 illustrates the observations of portfolio performance discussed above. The small quality portfolio *SQ* has the highest cumulative returns over the sample period. A 1€ investment

Figure 8: Cumulative return size sorted portfolios 80/20



in May of 2006 will be worth 4.7€ end of December 2021, a return of 370%. The portfolio with the second-highest return is the big quality portfolio *BQ*, with a return of 150%. Further, an investment in the market proxy yields higher returns than an investment in any junk portfolio. Especially the *BJ* portfolio only delivers minimal cumulative returns, achieving only 19 cents excess return over the sample period. Interestingly, the cumulative market returns are almost identical to a return into the QMJ factor, while both perform worse than the small stock long-short strategy *SQMJ*.

Comparing the exposure to the market factor within the size sorted portfolios, the big portfolios have larger market betas than the small portfolios. This was expected, as the big sample, by construction, contains a high percentage of the total market capitalization. The big sample portfolios need to show a higher covariance to the market factor than the small sample portfolios. The size betas in table 17 are only significant for the small portfolios. The small quality portfolio has a size beta of 0.598, so the portfolio returns correlate to 60% with the returns of the size factor. The size factor does not explain the returns of the big portfolios, as all coefficients are insignificant.

Lastly, the value factor is again only significant for the quality portfolios, confirming the result of Novy-Marx (2013, 2014a) that the value factor is negatively correlated with high quality, even after controlling for size. The same is true for the long-short strategies, indicating that these strategies are indeed quality investing strategies. Investing in quality while shorting junk is shown to be a profitable strategy, which is in line with the finding of Asness et al. (2018b), Novy-Marx (2014a) and others.

Table 17: Fama-French 3 factor model - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.714***	0.695***	−0.019	0.824***	0.844***	0.019	0.0001
	(0.044)	(0.041)	(0.037)	(0.056)	(0.047)	(0.052)	(0.034)
SMB	0.682***	0.598***	−0.084	−0.055	−0.140	−0.085	−0.084
	(0.114)	(0.107)	(0.098)	(0.146)	(0.123)	(0.136)	(0.090)
HML	0.064	−0.256***	−0.320***	0.133	−0.374***	−0.507***	−0.414***
	(0.092)	(0.087)	(0.079)	(0.118)	(0.099)	(0.109)	(0.073)
α	−0.001	0.004*	0.005***	−0.002	0.001	0.002	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.694	0.664	0.109	0.623	0.653	0.113	0.180

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows monthly Fama-French three-factor model regressions. These are time-series regressions of quality-sorted portfolio returns on the Fama-French factors. SJ is the small junk portfolio, SQ is the small quality portfolio, BJ is the big junk portfolio, BQ is the big quality portfolio, SQMJ is the small quality minus junk portfolio, BQMJ is the big quality minus junk portfolio, and QMJ is the average of SQMJ and BQMJ, the quality minus junk portfolio. The portfolios returns are weighted with their market capitalization as a fraction of the portfolio's total market capitalization. The alpha is the intercept of the time-series regression. The explanatory variables are the returns of the Market (MKT), Size (SMB) and Value (HML) factor portfolios. The sample period is from 2006 to 2021. A similar approach is followed for the other Fama-French three factor model tables in this thesis.

Comparing the factor betas for *SJ* and *SQ*, we see that both only significantly differ in the value beta. *SQ* has a negative value beta, while it is insignificant for *SJ*. Normally a negative factor beta should lower the predicted expected excess return of a portfolio, but the expected excess value factor returns are negative in our sample. The difference in performance between both portfolios can not be explained by returns to other factors but rather by the excess returns to the quality portfolio.

To illustrate the effect of the Fama-French factors on the portfolio returns, we show equation for portfolio *SQ* below:

$$r^e_{SQ} = 0.004 + 0.695\, r^e_{MKT} + 0.598\, r_{SMB} - 0.256\, r_{HML} + \epsilon_i \tag{74}$$

Our results show that quality outperforms junk. Our long-short strategies now show significant expected returns in excess of the explanatory factors. Investing in high quality while shorting junk has significant positive monthly alphas, even more pronounced when investing in the small sample. On the other hand, a long-short strategy in the big sample does not generate significant monthly returns in excess of the other explaining factors. This indicates that our sample shows a size premium as described by Banz (1981) and Asness et al. (2018a). Further results for the

CAPM and Fama-French five-factor models can be found in the appendix, in tables 45 and 46.

6.3 Robustness Checks

In the last section, we showed that quality investment strategies that buy and hold portfolios sorted by quality within a sample of low market capitalization companies, or take long positions in high-quality portfolios and short positions in low-quality portfolios, can generate high risk-adjusted returns and significant monthly alphas.
The following section tests if these results are robust to different model specifications. If the results do not show significant changes, we can infer that going long quality while shorting junk in our model can provide significant monthly excess returns regardless of the methods used.

6.3.1 Size split 90/10

As a first robustness check, we will change the size break point of our benchmark sample so that the big portfolios consist of the highest 10% firms by market capitalization, while the small portfolios consist of the other 90% consistent with Hsu et al. (2018) and Kozlov and Petajisto (2013).

Table 18: Performance measures size sorted 90/10

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
monthly							
ER	0.004	0.009***	0.005***	0.001	0.005	0.003	0.004**
	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)
CAPM α	−0.0002	0.005**	0.006***	−0.003	0.001	0.004	0.005**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Fama 3 α	−0.001	0.003*	0.004**	−0.003	0.000	0.003	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Fama 5 α	−0.0004	0.002	0.003	−0.004	−0.001	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
annual							
ER^{annual}	0.044	0.108	0.064	0.018	0.059	0.041	0.053
SR^{annual}	0.253	0.667	0.672	0.082	0.318	0.307	0.579
CAPM α	−0.0024	0.06	0.072	−0.036	0.012	0.048	0.06
Fama 3 α	−0.012	0.036	0.048	−0.036	0.000	0.036	0.048
Fama 5 α	−0.0048	0.024	0.036	−0.048	−0.012	0.036	0.036

Note: *p<0.1; **p<0.05; ***p<0.01

The results of the adjusted size split regressions are shown in table 18. Comparing the expected excess returns to the results in table 16, we see that the annual small portfolio expected excess returns have slightly increased while the expected excess returns for the big portfolios have slightly decreased. The portfolios are possibly more diversified by including more companies into the small sample. The expected excess returns and Sharpe ratios for the long-short strategies, that were shown to be significant in our model, have decreased, with the highest Sharpe ratio in *SQMJ* with 67%, down from 75% in table 16.

Figure 9: Cumulative return size sorted portfolios 90/10

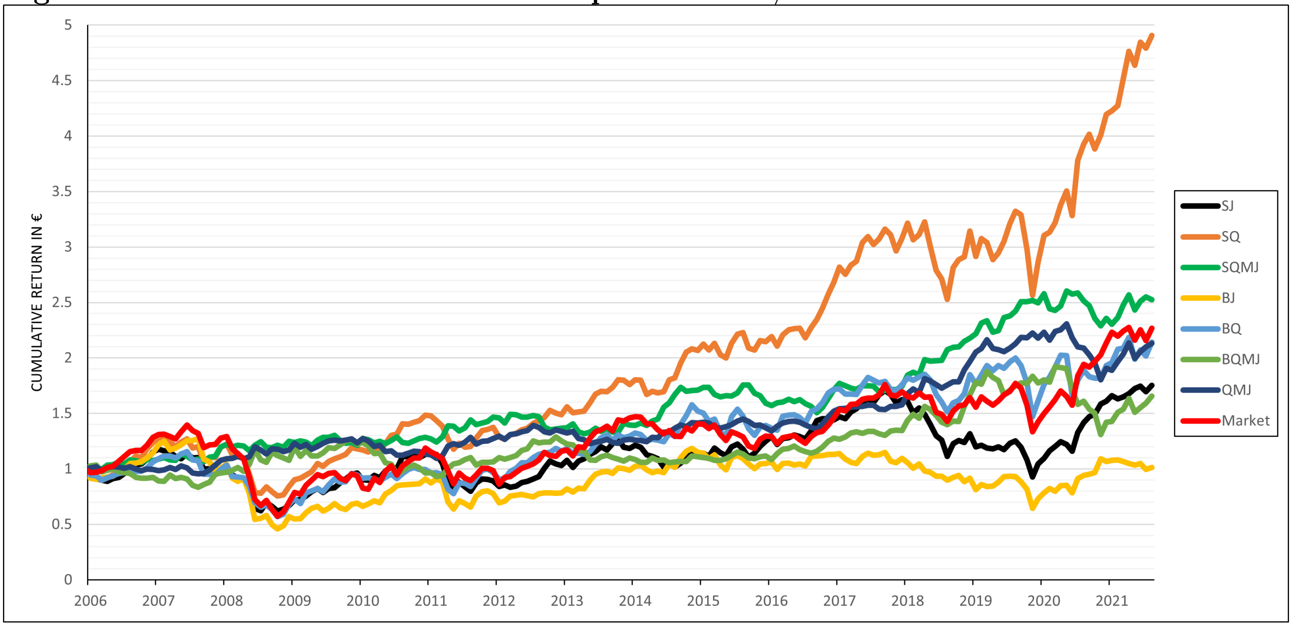


Figure 9 shows the cumulative returns for the adjusted 90/10 weights. Compared to our benchmark approach shown in figure 8, the cumulative returns are relatively stable. This result aligns with our prior assessment that changing the approach to a 90/10 sample has a limited impact on the portfolios' excess returns.

Looking at the monthly CAPM and Fama-French alphas, a difference between both the 80/20 and 90/10 size split can be seen in the Fama-French five-factor alphas. In table 18, the monthly five-factor alphas for *SQMJ* and *QMJ* are now insignificant, leaving no monthly five-factor alphas with a significant impact. The distribution of the remaining alphas is very similar to the 80/20 approach. Another factor explaining stock return variations is the SMB factor, showing similar betas compared to the 80/20 approach. Again the small portfolios have positive significant SMB factors, in lower magnitude as before. Including more big firms into the small portfolio has decreased the covariance between the SMB factor and the portfolio returns.

Apart from losing significance within the Fama-French five-factor framework, both the small size long-short strategy *SQMJ* and the *QMJ* factor still show high positive risk-adjusted returns. Even though the portfolios and strategies' performance and the factor loadings have

Table 19: Fama-French 3 factor model - size sorted 90/10

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.725***	0.757***	0.031	0.858***	0.846***	−0.012	0.010
	(0.044)	(0.040)	(0.039)	(0.059)	(0.050)	(0.057)	(0.037)
SMB	0.537***	0.454***	−0.083	−0.116	−0.216	−0.099	−0.091
	(0.115)	(0.104)	(0.103)	(0.154)	(0.130)	(0.149)	(0.096)
HML	0.009	−0.395***	−0.404***	0.100	−0.360***	−0.459***	−0.431***
	(0.092)	(0.084)	(0.083)	(0.124)	(0.105)	(0.120)	(0.077)
α	−0.001	0.003*	0.004**	−0.003	−0.00001	0.003	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.680	0.694	0.116	0.610	0.629	0.088	0.167

Note: *p<0.1; **p<0.05; ***p<0.01

slightly changed by adjusting the size breakpoint for the quality portfolios, the results are robust overall. Strategies going long quality and shorting junk generate returns in excess of the Fama-French three-factor model, and the size premium for small firms still exists. Results for the CAPM and Fama-French five-factor models can again be found in the appendix in tables 47 and 48.

6.3.2 Size split Median

In section 6.3.1, we increased the size of the small sample while decreasing the big sample. We now go in the opposite direction by defining the median of total market capitalization as the cut-off line between big and small samples. This approach is used by Asness et al. (2018b) for the US market. This test will show whether it is also appropriate for the German market.
Table 20 shows the performance measures for the portfolios sorted by size based on the median as the sample intersection point.

Compared to the performance of our 80/20 size approach shown in table 16, we again see similar tendencies in the results. Both quality portfolios outperform the junk portfolios, with annual expected excess returns of 10.8% for small quality and 7.9% for big quality. The small quality portfolio still outperforms the big quality portfolio. Additionally, the long-short strategies *SQMJ* & *QMJ* have larger alphas that do not lose their explanatory power of a monthly basis in the Fama-French five-factor model, unlike in the 90/10 size approach.

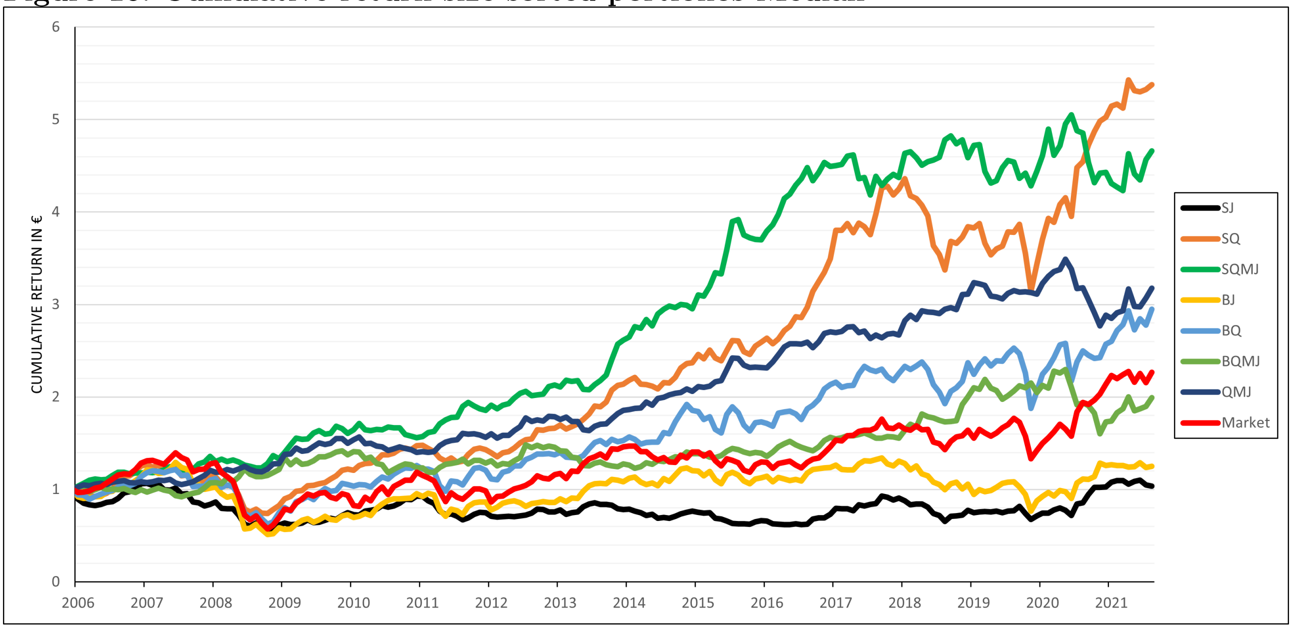
The cumulative returns of the median-sorted quality portfolios and strategies are shown to be more extreme in figure 10 compared to any of the approaches discussed so far. The cumulative returns are much more spread out, and as discussed above, the small portfolio long-short

Table 20: Performance measures size sorted Median

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
monthly							
ER	0.0005	0.009***	0.009***	0.002	0.007*	0.004*	0.006***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)
CAPM α	−0.002	0.006***	0.009***	−0.002	0.002	0.005*	0.007***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Fama 3 α	−0.003	0.005***	0.008***	−0.002	0.001	0.003	0.006***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Fama 5 α	−0.002	0.005**	0.007***	−0.003	0.001	0.004	0.006***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
annual							
ER^{annual}	0.006	0.108	0.104	0.027	0.079	0.051	0.077
SR^{annual}	0.043	0.798	1.023	0.139	0.434	0.430	0.932
CAPM α	−0.0024	0.072	0.108	−0.024	0.024	0.06	0.084
Fama 3 α	−0.036	0.06	0.096	−0.024	0.012	0.036	0.072
Fama 5 α	−0.024	0.06	0.084	−0.036	0.012	0.048	0.072

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 10: Cumulative return size sorted portfolios Median



strategy *SQMJ* and the *QMJ* factor perform better than before. As in the previous size specifications, the best performing portfolio best is the *SQ* portfolio, with a 437% return over the sample period. Again, we see that investing in quality achieves higher risk-adjusted returns than the market, indicating that investors can outperform the market with quality-sorted investment.

Overall, the size-sorting based on the median split has led to more extreme returns, including larger alphas in the small long-short strategy *SQMJ* and the quality-minus-junk *QMJ* factor. Even though the median sorted approach is usually utilized for the US market, the results indicate that it is also an appropriate sorting vehicle for the German market. Going long quality and shorting junk generates even higher returns in excess of the other factors. As the coefficient signs and returns are in line with our 80/20 size-sorted benchmark returns, the change of the intersection point to the median has shown the robustness of our results. For more detailed results on the CAPM, Fama-French three-factor and Fama-French five-factor models, please refer to the appendix in tables 49, 50 and 51.

6.3.3 Sample split Industries

So far in our analysis, we have looked at the German market as a whole[32]. However, certain investors are experts in a particular field and want to focus their investments in a specific industry[33].
As an additional robustness check of our investment approach, we split the sample before starting our conditional sort on size and quality. Our accounting data from *Compustat* covers the GIC sector coefficient[34], so we can split our sample into different industries. Of the 653 firms in our sample, 155 are classified as Industrial firms (*Sector 20*) and 154 firms as Information Technology (IT) firms (*Sector 45*). We focus on these two industries because the sample size for other industries is too small. The industry-specific analysis repeats the approach from section 6.2.3. This entails that the results of section 6.1, the derivation of our combined quality score, are assumed to hold within the specific industries. We create a separate sample for Industrial and IT firms before sorting conditional by size and quality.

First, we examine the quality investing performance within the sector of Industrial firms.
The results, shown in table 21, are similar to before. It is noticeable that the junk portfolios perform better than in table 16. However, the monthly expected excess returns of the *SJ* are insignificant. Nevertheless, small (big) quality portfolios have higher expected excess returns than the corresponding small (big) junk portfolios.

Looking at the different monthly alphas, we see that the long-short strategies lose significance and can not explain the difference in performance between the strategies. The 80/20 size sorting approach is possibly not appropriate for the distribution of companies within the sample of Industrial companies. A further investigation into specific size sorting within industries would

[32]while excluding financial firms
[33]Refer to Baca, Garbe, and Weiss (2000) and Vyas and Baren (2021) for industry-focused factor investing strategies
[34]`https://www.msci.com/our-solutions/indexes/gics`

Table 21: Performance measures Industrials size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
monthly							
ER	0.005	0.008*	0.003	0.005	0.007	0.002	0.002
	(0.005)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
CAPM α	0.001	0.004	0.003	0.0001	0.002	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Fama 3 α	0.0001	0.002	0.002	-0.0003	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Fama 5 α	-0.001	0.001	0.002	-0.001	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
annual							
ER^{annual}	0.062	0.095	0.033	0.061	0.080	0.019	0.026
SR^{annual}	0.279	0.474	0.233	0.246	0.369	0.097	0.211
CAPM α	0.012	0.048	0.036	0.001	0.024	0.024	0.036
Fama 3 α	0.001	0.024	0.024	-0.003	0.012	0.024	0.024
Fama 5 α	-0.012	0.012	0.024	-0.012	0.012	0.024	0.024

Note: *p<0.1; **p<0.05; ***p<0.01

exceed the focus of this thesis. For the results of CAPM, Fama-French three-factor and Fama-French five-factor models, please refer to tables 52, 53 and 54 in the appendix.
The second industry we examine in order to account for a different data cutting approach, is the IT sector.

Throughout our size sorted approach, the quality portfolios show higher expected excess returns than the corresponding junk portfolios. However, unlike in the full sample analysis, the big junk and quality portfolios have almost the same annual expected returns. Furthermore, the market betas are close to 1, as it can be seen in the Fama-French three-factor model in table 56 in the appendix. Since SAP SE and Infineon Technology AG dominate the IT sector by market capitalization, the expexted returns to the big portfolios consist primarily of the expected returns of these two companies. The portfolio structure in the big IT sample is therefore very unbalanced. Nevertheless the expected monthly excess returns for both the BJ and BQ are insignificant. It is interesting to note that the Sharpe Ratios for the BJ and BQ portfolios in table 22 are relatively low, even though they have an expected annual excess return of over 9%. The reason is that the BQ is less diversified in table 21 and therefore more volatile and risky, therefore implying higher volatility compared to SQ.

Different from the Industrial firm sector, we see some significant monthly alphas within the

Table 22: Performance measures IT size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
monthly							
ER	0.005	0.012***	0.006*	0.008	0.008	0.0003	0.003
	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.004)
CAPM α	0.001	0.008***	0.007*	0.002	0.004	0.001	0.004
	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
Fama 3 α	0.001	0.006**	0.005	0.002	0.002	−0.001	0.002
	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
Fama 5 α	0.0003	0.005*	0.005	0.004	0.001	−0.002	0.001
	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
annual							
ER^{annual}	0.066	0.139	0.073	0.092	0.096	0.003	0.038
SR^{annual}	0.278	0.713	0.421	0.313	0.364	0.012	0.216
CAPM α	0.012	0.096	0.084	0.024	0.048	0.012	0.048
Fama 3 α	0.012	0.072	0.06	0.024	0.024	−0.012	0.024
Fama 5 α	0.003	0.06	0.06	0.048	0.012	−0.024	0.012

Note: *p<0.1; **p<0.05; ***p<0.01

IT sample for both SQ and $SQMJ$ in a CAPM regression. Going long quality while shorting junk can deliver expected monthly excess returns not explained by other factors for the CAPM, but this disappears with the inclusion of Fama-French factors. On the other hand, the performance of the small quality portfolio compared to the small junk portfolio can again not be explained by factor betas. Hence, an investment into SQ delivers risk-adjusted excess returns. Overall, our quality investing approach based on a conditional sort first by size and then by quality works, even when only parts of our sample are examined. Our quality portfolios deliver higher expected excess returns than our junk portfolios, a result unchanged by the smaller sample size. Nonetheless, we prefer the 80/20 size split analysis from section 6.2.3. It allows for optimal diversification across multiple sectors and prevents portfolio returns in sectors such as IT from being dictated by individual companies due to high market capitalization.

Different approaches for sample sorting and cutting our data have not changed the model results concluded in our main analysis. Therefore, we can confidently say that strategies going long quality and short junk provide significant risk-adjusted returns in our German sample, especially within small stocks.

7 Discussion

After having found results for our quality investing approach and assessed the robustness of these results using different model specifications, we will now enter the discussion of our thesis. We start in section 7.1 by discussing the data and investment approach used in our paper, to address our choice for specific variables needed in our calculations, and the assumptions needed for our investing strategy.
Next in section 7.2, we explain the choice of quality factors and the specific metrics, that the factors consist of.
Afterward in section 7.3, we summarize our empirical results and give possible explanations and interpretations.
Lastly in section 7.4, we offer potential topics for future research.

7.1 Data and Investment approach

Our quality investing approach is dependent on the availability of accounting data. If the *Compustat* database does not provide data for a German company, the company can not be included in our sample. We use annual accounting data for our sample from 1999 to 2020, but downloading quarterly accounting data from the *Compustat* database would also be possible. As most firms are unlikely to report all accounting measures needed on a quarterly base, this would result in a smaller sample size and more missing accounting variables. Using quarterly data as in Asness et al. (2018b) would have the advantage of ranking companies four times a year. It would be possible to determine whether a company remains a quality company or changes to the junk sample more quickly.

To obtain more robust results, we could also increase the sample size. The time period was chosen to ensure that all share prices are denominated in Euro, so no currency conversion from Deutsche Mark to Euro has to take place. In addition, the Euribor was first published in 1999, which is the first fiscal year included in our analysis. We use the Euribor as the risk-free rate. In contrast, for the United States, the U.S. Treasury bill rate is typically used as the risk-free rate, as in Asness et al. (2018b). The treasury bill rate is the rate at which a government borrows money. Since it is unlikely that a sovereign defaults on such obligations, treasury rates can be considered risk-free rates (Hull (2015),p.178). In practice, however, treasury rates are often considered very low, so LIBOR and swap rates can also be used, although it is not possible to invest in them directly (Hull (2015),p.180).

Since the approach to calculating the growth score in Asness et al. (2018b) requires six years of accounting data, only companies with seven or more observations are included in the sample.

Companies with a recent IPO are therefore likely excluded. In order to include all companies with recent IPOs, one could loosen the growth definition and require fewer years of prior observations. Excluding the growth score completely to account for more firms would harm the performance of the quality score, as the growth factor shows a positive effect on stock prices, discussed in section 6.1.

We do not only limit the sample size in regards to the growth score, but also by excluding financial firms. For the factors included in our quality score, financial firms likely would display very different values. Financial firms have f.e. often much higher leverage levels, or do not have costs of goods sold, as they do not incur production costs. It is therefore considered consistent to exclude financial firms from our sample as in Fama and French (1992), Chen and Novy-marx (2011), Novy-Marx (2013) andKozlov and Petajisto (2013), but an extension solely into the effects of quality investing within the financial sector could nonetheless be interesting.

Our investment approach is consistent with Fama and French (1992) since we match all accounting data in year t-1 and start investing in year t. Importantly, we can only invest based on information that we know at the time. The German Commercial Code (HGB) requires all companies listed in Germany to publish their annual financial statements in the first four months of the following year[35]. To start investing directly after these four months is the intuitive approach, even though other papers such as Fama and French (1992) only start investing in July of year t. If we start investing directly after these four months, we can profit in our long portfolios immediately after the annual reports are published. However, since we match all accounting data to the end of December, the investment gap may be larger than four months for companies whose fiscal year ends before December, so the advantage of the shorter reaction horizon might disappear.

The literature usually distinguishes between two different types of investors. There are long-only investors, who buy and hold stocks they believe will go up in price, and there are long-short investors, who will additionally short the stocks they believe will fall in price. Our approach will apply this framework by buying only quality stocks and shorting junk stocks. This distinction is important because it has real-world implications. Many investors may not be able to short stocks or face a constraint to long positions (Kozlov & Petajisto, 2013). In reality, shorting may also be costly and difficult because not every stock can be shorted, and a shorting opportunity only exists if another investor is willing to lend the stock (Pedersen (2015), p.117).

When comparing the two types of investors, Novy-Marx (2014a) points out that both face fun-

[35]§325, `https://www.gesetze-im-internet.de/hgb/__325.html`

damentally different investment problems. A long-short investor is completely unconstrained because of the ability to separate exposure from opportunity decisions. This investor can control risk through leverage, and therefore is able to focus on finding new opportunities with the highest Sharpe ratios. In contrast, long-only investors cannot separate risk decisions from opportunities. Therefore, they must evaluate possible investments by considering risk and reward together. Investors could then pass up an investment with a higher Sharpe ratio to take a higher exposure to a lower Sharpe ratio investment. In order to reflect both groups of investors, both long-only portfolios and long-short portfolios are included in this thesis. To evaluate our quality-sorted portfolios we consider the CAPM (see section 3.3), the three-factor Fama-French model (see section 3.4), and the five-factor Fama-French model (see section 3.5). The five-factor model in particular has shown good performance in explaining returns (Fama & French, 2015). In order to focus on the results deemed most relevant by us, we include the Fama-French three-factor results in our main approach, and therefore only rarely discuss the RMW and CMA factors. Even though both factors show sometimes significant betas, the interpretation of these betas was not considered central for our approach.

For our portfolio regressions, we downloaded the Fama-French European Factors data from the Fama French Database. While these European factors can be used as a proxy for the German MKT, SMB, HML, RMW, and CMA factors, a separate calculation for the German market might result in slightly different and more appropriate returns for the German market. In particular, using a different market proxy such as the German DAX40 or a value-weighted market return of the entire German equity universe could have a significant impact and lead to market betas above 1, and possible higher expected excess returns. Nonetheless, the Fama-French factors are widely in asset pricing literature. For consistency, we decided to use the same database for all factors, therefore against calculating solely the MKT factor in a different way.

As discussed in section 5.1.4, the ESG score we use in our thesis is calculated by Refinitiv Eikon. We do not see the need to backtest or repeat the score, as this would entail unreasonable effort and time. We, therefore, assume the integrity of the score due to the resources invested by Refinitiv (2021). The combined ESG score is not the only score related to Environmental, Social or Corporate Governance performance provided by Refinitiv Eikon, detailed in section 5.1.4. One could therefore include multiple scores, and then differentiate the effects between the components of ESG. This approach could potentially explain more returns compared to the combined ESG score. Nonetheless, adapting all ESG scores is likely not possible in our sample, as these additional scores are less available than the combined ESG score for the German market, resulting in an even smaller sample.

7.2 Quality factors

In section 2, we conducted an extensive literature review of the various profitability, growth, safety, and ESG metrics that have been used in the literature as proxies for quality. Overall, we concluded that the metrics included in Asness et al. (2018b) explain the factors well, so we included their corresponding proxies except for the BAB, the GMAR, and the GMAR growth factors due to the reasons mentioned in section 2. One consequence of the exclusion is, that our score slightly differs from Asness et al. (2018b). We can therefore not directly compare our performance measures with Asness et al. (2018b). As this paper is the only of our knowledge, that examines the German market, we nonetheless give an indication how our QMJ factor compares to the QMJ factor of the authors, in order to give a performance benchmark. For a completely comparable score, we would have to drop the examination of every proxy and then calculate the factor exactly as in Asness et al. (2018b).

Most papers only look at the individual factors, such as in Hsu et al. (2018), as proxies for quality without aggregating them into a combined quality score. Asness et al. (2018b) though has succeeded in forming a combined quality score that includes proxies for profitability, growth, and safety. However, it is also possible that some of the variables are highly correlated and thus redundant. If this is the case, those variables could be dropped to ensure the variables explanatory power. Therefore, we examine the correlations of the metrics within profitability, growth, and safety to possibly construct these factors with fewer metrics while ensuring adequate explanatory power, as in Hsu et al. (2018). The easiest way to determine how metrics contribute to a factor is to determine the correlations between the calculated z-scores. If two z-scores are highly correlated, the metrics contribute in the same way to the combined factor. In line with the calculation of the individual metrics, we also compute the pair-wise factor correlations for each year. We calculate a time-series average over all years to obtain one correlation value for the entire sample of the different metrics pairs.

Figure 11 shows the results for the profitability factor, which initially consists of the factors ROE, ROA, CFOA, GPOA and ACC. It can be seen that ROE and ROA are almost perfectly correlated with a correlation coefficient of 0.92. Since both ratios have net income in the numerator and differ only in the denominator, this high correlation is not surprising. The other profitability metrics are only slightly correlated. Overall, it would be possible to omit either the ROE or the ROA ratio without losing explanatory power. Figure 12 shows the correlations for the growth factor composed of ΔROE, ΔROA, $\Delta CFOA$ and $\Delta GPOA$. Here, the picture is essentially the same. While most of the ratios are only slightly correlated, ΔROE and ΔROA are highly correlated with a correlation coefficient of 0.96, similar to the corresponding profitability metrics. Therefore, one of these factors could be omitted.

Figure 11: Correlation profitability z-scores

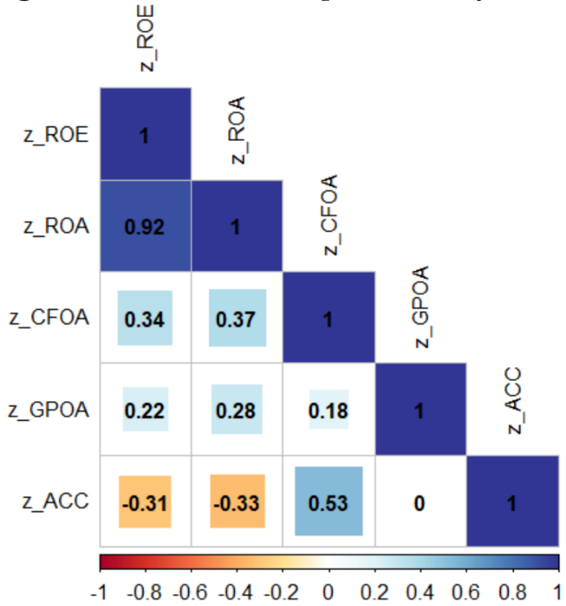


Figure 13 shows the results for the safety metric z-scores consisting of the Altman (1968) Z-score, Ohlson (1980) O-score, LEV and EVOL. Here, the picture is somewhat mixed without high correlations. Ohlson (1980) O-score and Altman (1968) Z-score with 0.54 and the O-score and the leverage with 0.55 show the highest correlations within the safety factor. The inclusion of all metrics is reasonable as those all contribute in different ways to the combined safety factor. One can conclude that a narrower definition of the profitability and growth factors could be possible. However, it could also be true that this thesis omits profitability, growth, or safety metrics that could provide additional explanatory power.

The z-scores for the individual factors profitability, growth, safety and ESG are used, to be able to combine the specific metrics without having to account for different scales. Using the ranking procedure described in section 5.1, the z-scores give the relative performance within a metric for each firm, which allows for an easy interpretation. By using z-scores, we follow Asness et al. (2018b), as the authors are able to create a combined quality score based on this approach. But this procedure could be too extensive and not necessarily needed. Instead of creating z-scores, one could choose a different approach, by f.e. ranking the performance within each metric, and afterward summing up all ranks for one firm. By ranking the sum of ranks for each factor, we would similarly create a measure that compares the firms based on their accounting based metrics. This approach might produce similar results compared to the z-score approach, and therefore seems to be a valid alternative, should the creation of z-scores not be possible for any reason.

In our approach, we use the quality factor z-scores to create our composite quality score.

Figure 12: Correlation growth z-scores

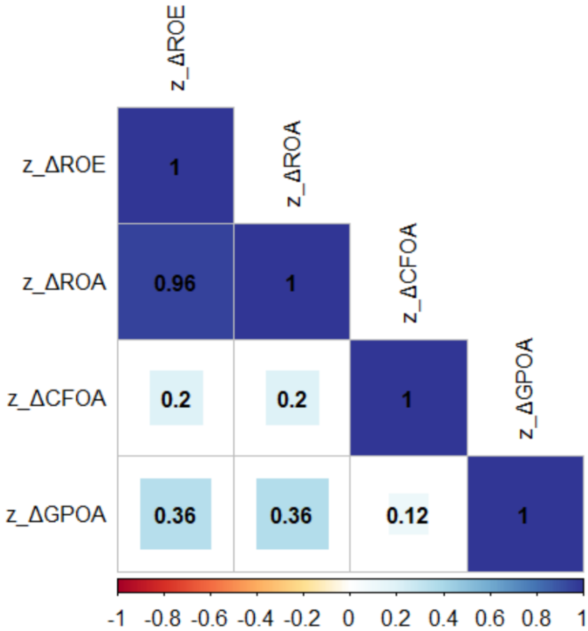
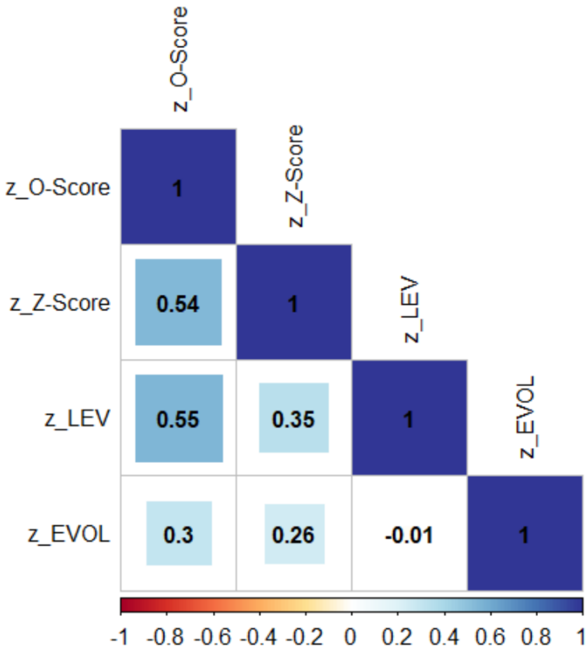


Figure 13: Correlation safety z-scores



While we show, that the factors separately and when included together in a regression are linked to higher stock prices, we do not conduct a similar analysis to include the individual factors when investing on quality-sorted portfolios. When creating these portfolios, we only sort on our composite quality score, while it would also be possible to create portfolios for the factors separately. This would allow us to determine, which quality factor is explaining the majority of returns to quality-sorted portfolios in our sample. Asness et al. (2018b) uses a similar approach including the factors separately, but finds the results to stay constant compared to the combined quality factor approach. Because this approach would be extensive and possibly lacking the robustness of combining all three factors into one score, we have decided against it's inclusion.

7.3 Empirical results

This section discussed the empirical results of section 6.
The approach of this paper was to define a quality score that could be used as the base of a strategy going long stocks of high quality while shorting those with low quality. This was established, by examining metrics used as proxies for profitability, growth, safety in Asness et al. (2018b), and including those we found to be relevant. As the three factors showed a significant impact on higher stock prices, they were aggregated into our quality score (section 6.1). Investing based on our quality score shows promise, as portfolios sorted by our quality definition deliver a Sharpe ratio for *QMJ* of 0.64 in Germany, compared to the Sharpe ratio of *QMJ* of 0.61 in Germany in Asness et al. (2018b). A direct comparison cannot be made, as the period in scope is slightly different and very limited information about the firms included in the German sample is given.

Additionally, we discussed an ESG score in our literature examination, which is not included in Asness et al. (2018b) quality definition.
Including an ESG as a factor into our model has not had the expected effect. Data availability limits the potential of using the ESG score in our benchmark sample. In order to connect the ESG score to changes in stock prices, we had to utilize a smaller sample only including ESG firms. Contrary to our expectation the effect of ESG on stock prices in the small sample was negative, but we are unable to compare that performance to our benchmark sample. It is unclear to us, if the negative effect is due to specifics within the small sample, or part of a bigger misconception regarding ESG scores. As it can be inferred from the construction of the ESG score discussed in section 5.1.4, the methodology benefits firms, that have had an ESG scores for multiple years. Since 2018, the availability of the ESG score within the German sample increased exponentially, as figure 4 shows. Therefore, the firms might on average have low scores, just because the firm's ESG score was only introduced recently.

ESG performance has become more prominent with investors in recent years, which could have let to a run on stocks with high ESG scores. Pedersen et al. (2021) argues, that investors with higher ESG preferences are willing to accept a lower Sharpe ratio for an investment into high ESG score portfolios. This increases the overall demand for these stocks among investors, which in turn lowers the expected return for these stocks, if a market has many ESG focused investors. Somewhat the opposite of high ESG stocks are the sin[36] stocks. Pedersen et al. (2021) argues, that high returns to sin stocks are due to the low demand for such stocks, implying that the high demand for ESG stocks leads to the opposite effect on returns. A different possible explanation for the ESG score results is that the market fails to price in, that high ESG score stocks are also more profitable. Then the stock price would be underpriced, leading to the observed relationship (Hanson & Dhanuka, 2015). While this topic is very interesting for us, it is also outside the scope of our paper.

To account for other explanations for the ESG score effect within our benchmark sample, we include an ESG score dummy as discussed in section 6.1. We find that having an ESG score increases the stock price, controlling for profitability, growth and safety. Arguing for a positive impact of the ESG score on stock prices omits two important aspects. First, the firms not having an ESG score should not necessarily be punished. Second, the dummy misses the differences of scale between the values. Having an ESG score should therefore not automatically be associated with a positive interpretation. Controlling for quality, size and dividend-payers, the ESG dummy variable does not have an effect on stock prices.
Overall, it was consistent to not include the ESG score into our quality score.

After having defined our quality score consisting of profitability, growth and safety metrics, we construct our quality-sorted portfolios. We start of by using value-weighted portfolios sorted for quality, but this approach shows limited significance in expected monthly excess returns and alphas. Further, the portfolio expected excess returns are not increasing in quality. The use of value-weighted quality portfolios might be ill-fitted, as common quality investing work such as Asness et al. (2018b) or Novy-Marx (2014a) use portfolios conditionally sorted on size and then on quality. Possibly, the analysis of the value-weighted quality-sorted portfolios could be omitted, in favor of only using portfolios conditionally sorted on size and quality. We adapt our approach by using equally-weighted portfolios.

The equally-weighted portfolios show the patterns expected, where higher quality portfolios are related to higher expected returns. As discussed in section 6.2.2, the results of the equally-weighted portfolio approach need to be discussed with caution. First, keeping equal weights across the portfolio at all times is difficult to achieve, and second, keeping equal weights may not be possible at all, especially for very small stocks. The equally-weighted approach in section 6.2.2 should be considered a theoretical illustration of quality investing where higher weights do not prioritize big firms. Therefore we only examine our size-sorted investment portfolios within the value-weighted approach.

[36]Those stock belong to the alcohol, gaming, tobacco or weapons industries,among others

Our main approach splits the sample into the 20% biggest and 80% smallest stocks by market capitalization. Going long portfolios with high quality and short portfolios with low quality delivers significant risk-adjusted returns not explained by CAPM or Fama-French factors, only when the sample is sorted on size (section 6.2.3). Quality has outperformed junk within the small sample after explaining for factor exposures, but this does not hold within the big sample, indicating a size effect in our sample. Our SQ portfolio shows significant expected excess returns in every specification, and so do the two long-short strategies SQMJ and QMJ. The QMJ portfolio is created similar to the QMJ factor from Asness et al. (2018b) and also delivers significant expected monthly excess returns, but of lower magnitude compared to the small sample long-short strategy. We test our results for robustness, by splitting the sample in two different ways in sections 6.3.1 and 6.3.2, and by cutting our data based on industry sectors in section 6.3.3.

In the robustness tests that adjust our sample split, we first change the distribution such that the big sample includes the largest 10% of companies, and the small sample includes the other 90% of firms. Second, we use the median as the cutting point, so that both samples include an almost equal amount of firms. Our results are robust for both approaches. The median approach shows higher annual Sharpe ratios for the SQ portfolio with 0.8 compared to 0.66, the SQMJ portfolio with 1.02 compared to 0.76 and the QMJ portfolio of 0.93 compared to 0.64, than in the main approach. It's conceivable, that the sample split at the median point is preferable to our main approach of an 80/20 split. We argue that this is not the case, as the median sample cutting approach is mostly used for the US market, as in Asness et al. (2018b), Novy-Marx (2013) or Hsu et al. (2018).
The characteristics of the German market are described closest by the 80/20 split, because the firms included in the main German index, the Dax 40, together represent around 80% of the German overall market capitalization (Deutsche Börse, 2021).

Additionally, an approach using only firms within specific industries was implemented. Within the Industrial and IT industry sector, the monthly strategy alphas show limited significance, questioning if industry-specific quality investing works. This test was implemented to see, if our results are robust for different data cutting approaches. The German market is characterized by a few very big firms with high market capitalization. Further, we see that the market displays high heterogeneity, so many different sectors are relevant within the German market. Even though we have focused on the sectors including the most companies, some portfolios consist of only few observations. In our sample, industry-based quality investing is therefore not well suited for the German market, but this approach could work on an European level.

Moreover, the expected annual excess returns and annual Sharpe ratios in our sample cannot be considered as realized returns. In reality, transaction costs are incurred by an investor when buying or selling a share. Li, Chow, Pickard, and Garg (2019) analyze the impact of transaction costs in different factor investment strategies in their paper, including a quality investment strategy. Their main finding was that with lower portfolio volumes, a higher turnover rate and a higher concentration of turnover increases the strategies' transaction costs increase. Moreover, the authors concluded that the more the portfolio weights deviate from a volume-weighted portfolio consisting of the most liquid stocks, the higher are the transaction costs. Li et al. (2019) present these results primarily for U.S.-based strategies but mention that they found similar results for international markets.

If a German investor wants to execute a buy or sell order on the largest German stock exchange, the Frankfurt Stock Exchange, that investor has to pay a brokerage fee of 0.08% of the share price. If the corresponding firm is included in the DAX, this fee drops to 0.04%. In addition, an investor can only trade shares through a bank as an intermediary. For this service, the bank charges 1% of the share price in most cases (Deutsche Börse AG, 2022).
Since we rebalance our portfolios every year, the transaction volume is possibly quite high. Therefore, the significant trading costs incurred would reduce the excess portfolio returns found in section 6.
This cost-problem is even more pronounced for the long-short portfolios. In addition to transaction costs, these portfolios also incur short-selling costs. D'Avolio (2002) show in their paper that these short-selling costs are modest in the U.S. market. 91% of the stocks borrowed by investors in the sample incur costs of less than 1% per annum. The other 9% of stocks, considered very special stocks, had an average borrowing cost of 4.3% per annum. In addition, some stocks were never shorted, especially small stocks with less than 1% share of the U.S. market capitalization. We were not be able to find similar information on shorting costs in the German market.

It is important to note that the possibility of not being able to short a stock depends not only on whether someone is willing to lend it but also on whether the regulations allow it. In March 2020, Austria, Belgium, France, Italy, Greece and Spain introduced a ban on short-selling to stop the exceptional decline in prices caused by the Covid-19 pandemic (Bessler & Vendrasco, 2021). Overall, transaction costs and shorting costs should be considered when making investment decisions, but the inclusion of these costs is not simple and goes beyond the scope of this thesis.

7.4 Further research

Lastly, we want to discuss possible extensions based on the results of our work, that were not the focus of our thesis.

First, the combination of quality and value investing strategies could be interesting for further research. Throughout our paper, we can see significant factor betas for the value factor HML when looking at our Fama-French three-factor model. Especially the high-quality portfolios display negative significant value betas, indicating that the returns of our high-quality portfolios are negatively related to the value factor returns. This result confirms the negative correlation found between quality and value, discussed among others in Novy-Marx (2013). Further, both Novy-Marx (2013, 2014a) and Asness et al. (2018b) find that combined value and quality investing strategies outperform pure quality strategies. Value investing strategies are shown by the authors to be ideal hedges for quality investing strategies. In Asness et al. (2018b), that sort of strategy is called *Quality at a reasonable price*, and are argued to be in line with the investing approach of famous value investor Warren Buffet. By defining a value factor specifically for our sample, it should be possible to develop a strategy based on both value and quality approaches.

Another topic for future research is related to the ESG score, examined in our paper for possible quality characteristics. As discussed in section 7.1, we were not able to analyze the ESG score in our benchmark sample, as only a limited number of companies had ESG scores available throughout the sample period. But as shown in figure 4, the number of firms with an ESG score has increased exponentially since 2018. It would be possible to perform our strategy with more firms including an ESG score in 5 to 10 years.

Lastly, our sample size could be expanded to not only include German but rather all publicly traded firms in Europe, since most quality investing literature so far focuses on the US. As discussed in section 7.1, we use European Fama-French factors, so the factor fit in our model could increase. An inclusion of more countries would also increase the sample size. This could be particularly interesting for quality investing based on industry specific samples, as we found that the German market lacks the amount of companies needed for an analysis into different sectors.

8 Conclusion

Quality is missing a univariate definition across investing literature. In this paper we conduct an extensive literature review into several proxies of factors linked to quality. These factors are measures for profitability, growth, safety and ESG. Instead of analyzing the measures separately, we construct a combined quality score, following the methodology developed by Asness et al. (2018b). This quality score consists of all factors that show a positive impact on stock prices. While the factors profitability, growth and safety command a higher stock price, the ESG factor does not. Regressing stock prices on our combined quality score, we find that quality over the whole sample commands a 22% increase in stock prices. Based on that result, we then create portfolios only sorted on quality, using value-weighted and equally-weighted portfolio rebalancing. Portfolios in the value-weighted approach showed mainly insignificant monthly excess returns and alphas, while performance measures for equally-weighted portfolios show significance. Further, a trend where quality portfolios outperform junk portfolios is present, but the implementation of equally-weighted portfolios is a difficult task in reality. But as the results display a size effect, we adapt our approach by conditionally sorting the sample first on size and afterward on quality, in line with analysis by Asness et al. (2018b) and Novy-Marx (2014a), among others.

For size-sorted samples, quality clearly outperforms junk. In the small sample, consisting of the 80% firms with the lowest market capitalization, the quality portfolio SQ delivers significant expected monthly excess returns, resulting in an annualized Sharpe ratio of 0.66. In addition, a long-short strategy in the small sample delivers an annual Sharpe ratio of 0.76. However, the big sample portfolios do not show significant expected monthly excess returns or alphas. Consequently, a long-short strategy within the big sample does produce insignificant results.
Our QMJ portfolio, combining the small and big sample long-short strategies, gives an annualized Sharpe ratio of 0.64, with significant monthly excess returns. This is in line with the results of Asness et al. (2018b), who find an annualized Sharpe ratio of 0.61 for their QMJ portfolio in the German market. Our results are robust for sorting differently on size and adjusting the sample size due to an industry specific focus.

Based on our quality definition, we were able to show that quality outperforms junk in the German market. Using a suitable approach, quality investing can be a profitable strategy in Germany, that can outperform a market proxy.

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9 Appendix

9.1 Appendix - Data

Figure 14: List of firms included in the analysis

Company Name	N	Company Name	N	Company Name	N	Company Name	N	Company Name	N	Company Name	N
118000 AG	6	CENTROSOLAR AG	1	FRESENIUS SE & CO KGAA	16	KOLBENSCHMIDT-PIERBURG AG	2	OTTO STUMPF AG	3	SPOBAG AG	3
11880 SOLUTIONS AG	16	CENTROTEC SUSTAINABLE AG	15	FRIWO AG	16	KOLN-DUSSELDORFER DEUTSCH	11	P&I PERSONAL & INFORMATIK AG	8	SPORT1 MEDIEN AG	9
2G ENERGY AG	8	CENTROTHERM INTERNATIONAL AG	2	FROSTA AG	16	KONTRON AG	12	PAION AG	3	SPORTTOTAL AG	4
2INVEST AG	14	CEOTRONICS AG	16	FUCHS PETROLUB SE	16	KPS AG	6	PARAGON AG	5	SQS SOFTWARE QUALITY SYS AG	7
3U HOLDING AG	16	CEWE STIFTUNG & CO KGAA	16	FUNKWERK AG	16	KROMI LOGISTIK AG	13	PARK & BELLHEIMER AG	9	STAATL MINERALBRUNNEN AG	16
4 SC AG	10	CINEMEDIA AG	3	GASANSTALT KAISERSLAUTERN AG	5	KRONES AG	16	PAUL HARTMANN AG	16	STADA ARZNEIMITTEL AG	15
7C SOLARPARKEN AG	10	CLEARWISE AG	4	GEA GROUP AG	16	KSB SE & CO KGAA	16	PC-WARE INFO TECHNOLOGIES AG	5	STEICO AG	12
7DAYS MUSIC ENTERTAINMENT A	7	CLIQ DIGITAL AG	10	GELSENWASSER AG	16	KTG AGRAR AG	4	PELIKAN AG	5	STEMMER IMAGING AG	1
A. MOKSEL AG	6	CLOPPENBURG AUTOMOBIL AG	9	GERATHERM MEDICAL AG	16	KTG ENERGIE AG	1	PFEIFFER VACUUM TECHNOLOGY	16	ST-GOBAIN OBERLAND AG	14
AAP IMPLANTATE AG	16	CO.DON AG	16	GERMAN VALUES PROPERTY GROUP	5	KUKA AG	16	PFERDEWETTEN.DE AG	12	STINAG STUTTGART INVEST AG	1
ABIT AG	1	COMARCH SOFTWARE AND BERATU	7	GERRESHEIMER GROUP	8	KULMBACHER BRAUEREI AG	16	PFLEIDERER AG	5	STO SE & CO KGAA	16
ABO WIND AG	3	COMPUGROUP MEDICAL SE & CO	16	GESCO AG	16	KWS SAAT SE & CO KGAA	16	PHOENIX AG	1	STOEHR & CO AG	7
ACTIVA RESOURCES AG	4	COMPUTERLINKS AG	5	GESUNDHEITSWELT CHIEMGAU AG	2	LANDSHUTER KUNSTMUEHLE AG	2	PHOENIX SOLAR AG	8	STRABAG AG	12
ACTRIS AG	5	COMTRADE AG	1	GFK SE	12	LANXESS AG	11	PILKINGTON DEUTSCHLAND AG	6	STRATEC SE	16
ADESSO SE	15	CONERGY AG	2	GFT TECHNOLOGIES AG	16	LECHWERKE AG	15	PIPER GENERALVERTRET DEUTSCH	11	STROEER SE & CO KGAA	5
ADIDAS AG	16	CONET TECHNOLOGIE AG	1	GIRINDUS AG	3	LEICA CAMERA AG	7	PIRONET AG	13	STUDIO BABELSBERG AG	6
ADLER MODEMARKTE AG	6	CONSTANTIN FILM AG	4	GK SOFTWARE SE	8	LEIFHEIT AG	16	PITTLER MASCHINENFABRIK AG	2	SUED-CHEMIE AG	6
ADM HAMBURG AG	16	CONTINENTAL AG	16	GLOBAL PVQ SE	2	LEONI AG	16	PIXELPARK AG	5	SUEDWESTDEUTSCHE SALZWERKE	16
ADVA AG OPTICAL NETWORKING	16	COR AG FINANCIAL	4	GOING PUBLIC MEDIA	12	LEWAG HOLDING AG	16	PLAN OPTIK AG	11	SUEDZUCKER AG	16
ADVANCED INFLIGHT ALLIANZ AG	3	COVESTRO AG	2	GRAMMER AG	16	LHA KRAUSE AG	1	PLENUM AG	16	SUESS MICROTEC SE	16
ADVANCED PHOTONICS TECH AG	2	CPU SOFTWAREHOUSE AG	16	GRAPHIT KROPFMUEHL AG	7	LINDE AG	13	PNE AG	9	SUNWAYS AG	6
AG F HISTOR WERTP	11	CROPENERGIES AG	9	GREIFFENBERGER AG	16	LINDNER HOLDING KGAA	4	PONGS & ZAHN AG	3	SURIKATE MITTELSTANDS AG	4
AGENNIX AG	2	CTS EVENTIM AG & CO KGAA	16	GRUSCHWITZ TEXTILWERKE AG	11	LINOS AG	4	PORSCHE AUTOMOBIL HOLDING SI	5	SURTECO SE	16
AGO AG ENERGIE & ANLAGEN	3	CURANUM AG	9	H&R GMBH & CO KGAA	16	LOEWE AG	8	POWERLAND AG	1	SWARCO TRAFFIC HOLDING	9
AHLERS AG	16	CURASAN AG	14	HAEMATO AG	12	LOTTO24 AG	3	PRAKTIKER AG	4	SYMRISE AG	11
AIXTRON SE	16	CURTIS 1000 EUROPE AG	3	HALLOREN SCHOKOLADENFABRIK	12	LPKF-LASER & ELECTRONICS AG	16	PRIMION TECHNOLOGY AG	5	SYNAXON AG	10
AKTIENBRAUEREI KAUFBEUREN	16	CYBIO AG	7	HAMATECH AG	3	LS INVEST AG	16	PRO DV SOFTWARE AG	2	SYZYGY AG	16
ALBA SE	16	CYCOS AG	9	HAMBURGER HAFEN UND LOGISTIK	14	LS TELCOM AG	15	PROCON MULTIMEDIA AG	7	TA TRIUMPH-ADLER AG	2
ALEO SOLAR AG	4	CYTOTOOLS AG	5	HAMMONIA SCHIFFSHOLDING AG	1	LUDWIG BECK AG	16	PROGRESS-WERK OBERKIRCH AG	16	TAKKT AG	16
ALEXANDERWERK AG	1	D&S EUROPE AG	5	HANSA GROUP AG	2	M1 KLINIKEN AG	2	PROSIEBENSAT.1 MEDIA SE	16	TDMI AG	3
ALIGNA AG	5	DALDRUP & SOEHNE AG	12	HANSEN SICHERHEITSTECHNIK AG	2	M4E AG	5	PSB AG	3	TDS INFORMATIONSTECHNOLOGIE	3
ALL FOR ONE GROUP SE	16	DATA MODUL AG	16	HANSEYACHTS AG	10	MAGIX AG	4	PSI SOFTWARE AG	16	TECHEM AG	3
ALLG GOLD & SILBERSCHEIDEAN	16	DATAGROUP SE	9	HAPAG-LLOYD AG	6	MAINOVA AG	10	PULSION MEDICAL SYSTEMS SE	15	TECHNOTRANS AG	16
ALLGAUER ALPENWASSER AG	6	DATRON AG	7	HAWESKO HOLDING AG	16	MAN SE	16	PUMA SE	16	TELEFONICA DEUTSCHLAND	6
ALLGAUER BRAUHAUS AG	8	DCI-DATABASE FOR COMM & IND	7	HEIDELBERG PHARMA AG	1	MANZ AG	11	PVA TEPLA AG	16	TELES AG INFORMATIONSTECHNOL	5
ALLGEIER SE	16	DEAG-DEUTSCHE ENTERTAINMENT	16	HEIDELBERGCEMENT AG	16	MARNA BETEILIGUNGEN AG	3	Q BEYOND AG	16	TEREX MATERIAL HANDLING	4
ALTANA AG	5	DEGUSSA AG	1	HEIDELBERGER DRUCKMASCHINEN	16	MARSEILLE-KLINIKEN AG	9	R STAHL AG	16	TERREX HANDELS-AG	2
ALUMINIUMWERK UNNA AG	9	DELIGNIT AG	9	HEILER SOFTWARE AG	8	MASCHINENFABRIK BERTHOLD	16	RALOS NEW ENERGIES AG	6	TEUTOBURGER WALD EISENBAHN	4
AMADEUS FIRE AG	16	DELIVERY HERO AG	2	HELIOCENTRIS FUEL ENERGY SOL	3	MASTERFLEX SE	5	RATIONAL AG	16	THYSSENKRUPP AG	16
ANALYTIK JENA AG	9	DELTICOM AG	8	HELLA GMBH & CO. KGAA	7	MATICA TECHNOLOGIES AG	5	READCREST CAPITAL AG	4	TIAG-TABBERT INDUSTRIE AG	1
ANZAG-ANDREAE-NORIS ZAHN AG	7	DERMAPHARM HOLDING	1	HELLOFRESH SE	1	MAX AUTOMATION	16	REALTECH AG	16	TISCON AG INFOSYSTEMS	3
AOVO TOURISTIK AG	2	DESIGN HOTELS AG	7	HELMA EIGENHEIMBAU AG	13	MAXDATA AG	3	REALTIME TECHNOLOGY AG	5	TOGNUM AG	2
ARBOMEDIA AG	3	DEUFOL SE	16	HENKEL AG & CO KGAA	16	MCKESSON EUROPE AG	10	REGENBOGEN AG	15	TOM TAILOR HOLDING SE	3
ARCANDOR AG	4	DEUTSCHE LUFTHANSA AG	16	HIRSCH AG	1	MCS SYSTEME AG	7	RENK AG	15	TONKENS AGRAR AG	6
ARTEC TECHNOLOGIES AG	13	DEUTSCHE POST AG	16	HMS BERGBAU AG	7	MDB AG	6	REPLY DEUTSCHLAND AG	8	T-ONLINE INTERNATIONAL AG	1
ARTNET AG	3	DEUTSCHE ROHSTOFF AG	8	HOCHTIEF AG	16	MEDIANTIS AG	2	REPOWER SYSTEMS SE	1	TRANSTEC AG	9
AS CREATION TAPETEN AG	16	DEUTSCHE STEINZEUG CREM & BR	5	HOFTEX GROUP AG	16	MEDICLIN AG	16	RHEINMETALL AG	16	TRIPLAN AG	11
ASIAN BAMBOO AG	4	DEUTSCHE TELEKOM	16	HOHNER (MATTH) AG	9	MEDIGENE AG	11	RHOEN-KLINIKUM AG	16	TRIUMPH INTERNATIONAL AG	5
ASKNET SOLUTIONS AG	7	DEUTZ AG	16	HOLCIM (DEUTSCHLAND) AG	7	MEDION AG	7	RIB SOFTWARE SE	10	TUI AG	15
ATOSS SOFTWARE AG	15	DIDIER-WERKE AG	5	HOLIDAYCHECK GROUP AG	15	MEDIQON GROUP AG	10	RICARDO.DE AG	4	TURBON AG	16
AUDI AG	15	DIEBOLD NIXDORF AG	10	HOMAG GROUP AG	5	MEDISANA AG	10	RODER ZELTSYSTEME SERVICE	9	TV LOONLAND AG	1
AUGUSTA TECHNOLOGIE AG	15	DIERIG HOLDING AG	12	HOME24 SE	1	MENSCH & MASCHINE SOFTWARE	16	ROHWEDDER AG	3	UESTRA HANNOVERSCHE VERKEHR	15
AUMANN AG	2	DIS-DEUTSCHER INDUSTRIE SERV	3	HORNBACH HOLDING AG & CO	16	MERCEDES-BENZ GROUP AG	16	ROPAL EUROPE AG	1	UMS UNITED MEDICAL SYS INTL	9
AURUBIS AG	16	DMG MORI AG	16	HORNBACH-BAUMARKT AG	16	MERCK KOMMANDITGESELLSCHAF	16	ROTH & RAU AG	5	UNIPER SE	2
AUTANIA AG	2	DOCCHECK AG	15	HOTEL.DE AG	2	METRIC MOBILITY SOLUTIONS AG	7	ROY ASSET HOLDING SE	2	UNITED INTERNET AG	16
AXEL SPRINGER SE	15	DOUGLAS HOLDING AG	8	HUCKE AG	1	METRO AG	1	RUECKER AG	7	UNITED LABELS AG	16
AZEGO AG	1	DR HOENLE AG	16	HUGO BOSS AG	16	MEVIS MEDICAL SOLUTIONS AG	9	RWE AG	16	UNIWHEELS AG	3
B&S BANKSYSTEME AKTIENGES	16	DR SCHELLER COSMETICS AG	3	HUMANOPTICS AG	11	MICROLOG LOGISTICS AG	1	SAG SOLARSTROM AG	7	UNYLON AG	2
BASF SE	16	DRAEGERWERK AG	16	HWA AG	12	MIFA MITTELDEUTSCHE FAHRRAD	7	SALTUS TECHNOLOGY AG	2	USU SOFTWARE AG	16
BASLER (VISION TECHNOLOGIES)	16	DUERR AG	16	HYDROTEC GESELLSCHAFT FUR WA	7	MINERALBRUNNEN UEBERKINGEN	16	SALZGITTER AG	16	UTIMACO SAFEWARE AG	7
BASTEI LUBBE AG	3	DURKOPP ADLER AG	13	HYMER AG	8	MME MOVIEMENT AG	10	SAP SE	16	UZIN UTZ AG	16
BAUER AG	15	DVS TECHNO AG	12	HYRICAN INFORMATIONSSYSTME	16	MOBOTIX AG	10	SAP SYSTEMS INTEGRATIONS AG	2	VA-Q-TEC AG	2
BAUMOT GROUP AG	8	DYCKERHOFF AG	8	I FAO AG	16	MOEBEL WALTHER AG	4	SARTORIUS AG	16	VATTENFALL EUROPE AG	2
BAYER AG	16	E.ON SE	11	IBS AG ENGR CONSLTG SOFTWARE	9	MOLOGEN AG	12	SCA HYGIENE PRODUCTS SE	8	VBH HOLDING AG	6
BAYER MOTOREN WERKE AG	16	EASY SOFTWARE AG	10	IBU-TEC ADVANCED MATERIALS	1	MORPHOSYS AG	16	SCHAEFFLER AG	1	VCL FILM & MEDIEN AG	3
BAYER SCHERING PHARMA AG	3	ECKERT & ZIEGLER AG	16	IDS SCHEER AG	5	MOSAIC SOFTWARE AG	2	SCHALTBAU HOLDING AG	7	VECTRON SYSTEMS AG	9
BAYERISCHE GEWERBEBAU AG	3	ECOTEL COMMUNICATION AG	11	IFA SYSTEMS AG	13	MOUNTAIN ALLIANCE AG	10	SCHLOSS WACHENHEIM AG	16	VERBIO VEREINIGTE BIOENERGIE	9
BAYWA AG	16	ECOUNION AG	2	IM INTERNATIONALMEDIA AG	2	MOX TELECOM AG	3	SCHLOTT GRUPPE	5	VEREINIGTE SCHMIRGEL	8
BBS KRAFTFAHRZEUGTECHNIK AG	1	EDDING AG	16	IMPREGLON AG	7	MPH HEALTH CARE AG	6	SCHULER AG	15	VERITAS AG	7
BEATE UHSE AG	11	EDEL SE & CO KGAA	13	INDUS HOLDING AG	16	MS INDUSTRIE AG	16	SCHULTE SCHLAGBAUM AG	15	VILLEROY & BOCH AG	16
BECHSTEIN(C)	9	EDOB ABWICKLUNGS AG	4	INFAS HOLDING AG	16	MSG LIFE AG	10	SCHUMAG AG	14	VISCOM AG	11
BECHTLE AG	16	EHLEBRACHT AG	4	INFINEON TECHNOLOGIES AG	16	MTU AERO ENGINES AG	11	SCHWABENVERLAG AG	11	VITA 34 AG	10
BEIERSDORF AG	16	EICHBORN AG	5	INFO AG	7	MUEHLBAUER HOLDING AG&CO	16	SCHWAELBCHEN MOLKEREI JAK	16	VK MUHLEN AG	9
BERENTZEN-GRUPPE AG	6	EIFELHOHEN KLINIK AG	16	INIT INNOVATION TRAFFIC SE	15	MUEHLHAN AG	11	SCHWARZ PHARMA AG	4	VOLKSWAGEN AG	16
BERTELSMANN SE & CO KGAA	16	EINBECKER BRAUHAUS AG	13	INNOGY SE	1	MUELLER - DIE LILA LOGISTIK	14	SCHWEIZER ELECTRONIC AG	16	VOLTABOX AG	1
BERTRANDT AG	16	EINHELL GERMANY AG	16	INNOTEC TSS AG	10	MUELLER WEINGARTEN AG	2	SCOUT24 SE	1	VOSSLOH AG	16
BERU AG	4	ELEPHANT SEVEN AG	1	INNOVATIV-DIGITALE MEDIEN AG	3	MUNCHENER TIERPARK HELLA	14	SECUNET SECURITY NETWORKS AG	16	VTG AG	14
BETA SYSTEMS SOFTWARE AG	16	ELEXIS AG	9	INTEGRATA AG	7	MVISE AG	1	SEDLBAUER AG	3	VTION WIRELESS TECHNOLOGY	4
BET-AT-HOME COM AG	10	ELEXXION AG	1	INTERCARD AG INFORMATIONSSYS	9	MVV ENERGIE AG	16	SEDO HOLDING AG	7	VWD VEREINIGTE WIRTSCHAFTSDI	2
BHB BRAUHOLDING BAYERN-MITT	5	ELMOS SEMICONDUCTOR SE	16	INTERSHOP COMMUNICATIONS AG	16	MYBET HOLDING SE	12	SEVEN PRINIPLES AG	12	W.E.T. AUTOMOTIVE SYSTEMS AG	8
BHS TABLETOP AG	15	ELRINGKLINGER AG	16	INTERTAINMENT AG	4	MYHAMMER HOLDING AG	7	SFC ENERGY AG	9	WACKER CHEMIE AG	15
BIEN-ZENKER AG	9	ELUMEO SE	3	INTICOM SYSTEMS AG	12	NABALTEC AG	11	SGL CARBON SE	16	WACKER NEUSON SE	12
BIJOU BRIGITTE MOD ACCESS AG	16	EMS NEW MEDIA AG	2	INVISION AG	9	NANOFOCUS AG	11	SHF COMMUNICATION TECH AG	8	WALLSTREET:ONLINE AG	13
BILFINGER SE	16	ENBW ENERGIE BADEN	16	IPC ARCHTEC AG	2	NANOGATE SE	8	SHS VIVEON AG	16	WAPME SYSTEMS AG	1
BIO-GATE AG	2	ENDOR AG	1	ISRA VISION AG	15	NANOREPRO AG	5	SHW AG	5	WASGAU PRODUKTIONS & HANDEL	15
BIOLITEC AG	5	ENERGIEKONTOR AG	16	ISRA VISION PARSYTEC AG	6	NEBELHORNBAHN	16	SIEMENS AG	16	WASHTEC AG	16
BIOTEST AG	16	ENVITEC BIOGAS AG	12	ITELLIGENCE AG	8	NEMETSCHEK SE	16	SILTRONIC AG	3	WAVELIGHT AG	3
BKN INTERNATIONAL AG	4	EPCOS AG	4	IVU TRAFFIC TECHNOLOGIES AG	16	NET MOBILE AG	7	SIMONA KUNSTSTOFFWERKE AG	16	WEBAC-HOLDING AG	16
BLG-BREMER LAGERHAUS-GESELLS	16	EPIGENOMICS AG	11	JENOPTIK AG	16	NET SE	7	SINGULUS TECHNOLOGIES AG	10	WEBER & OTT AG	4
BOCHUM GELSENKIRCHENER STRA	11	ERLEBNIS AKADEMIE AG	3	JETTER AG	8	NEUE SENTIMENTAL FILM AG	5	SINNERSCHRADER AG	15	WELLA AG	2
BOEWE SYSTEC AG	4	ERLUS AG	11	JOH. FRIEDRICH BEHRENS AG	14	NEW WORK SE	10	SIXT SE	16	WENG FINE ART AG	3
BORUSSIA DORTMUND GMBH & C	15	ESSANELLE HAIR GROUP AG	9	JOHN DEERE-LANZ VERWALTUN AG	1	NEXUS AG	15	SKW STAHL-METALLURGIE HLDG	5	WERU AG	1
BRAIN BIOTECH AG	3	ETIENNE AIGNER AG	7	JOST AG	16	NORCOM INFO TECH GMBH & CO	16	SKY DEUTSCHLAND AG	5	WESTAG AG	16
BRAUEREI MONINGER AG	13	EUROKAI KGAA	16	JUNGHEINRICH AG	16	NORDDEUTSCHE STEINGUT AG	15	SLM SOLUTIONS GMBH	2	WILLIAMS GRAND PRIX HLDGS	1
BREMER STRASSEN AG	12	EUROMICRON AG COMM & CTRL	14	K&S AG	16	NORDEX SE	15	SLOMAN NEPTUN SCHIFFAHRTS-A	16	WINDELN.DE SE	3
BRENNTAG SE	8	EVONIK INDUSTRIES AG	8	KAESSBOHRER GELAENDEFAHRZEUG	5	NORDWEST HANDEL AG	14	SMA SOLAR TECHNOLOGY AG	11	WINKLER & DUENNEBIER AG	4
BRILLIANT AG	13	EVOTEC SE	16	KAMPA AG	3	NORMA GROUP SE	8	SMT SCHARF AG	11	WINTER AG	2
BROADNET AG	2	F24 AG	7	KAP AG	16	NOVEMBER AG	1	SNP SCHNEIDER-NEUREITHER & P	16	WIRECARD AG	10
BRUEDER MANNESMANN AG	14	FASSON AG	1	KERAMAG-KERAMISCHE WERKE AG	3	NTT COM SECURITY AG	8	SOFTING AG	16	WMF AG	9
BUCH.DE INTERNETSTORES AG	9	FHW-FERNHEIZWERK NEUKOLLN AG	15	KHD HMBLD WDG VRMGSVRWLTG A	3	NUCLETRON ELECTRONIC AG	15	SOFTLINE AG	3	WOM - WORLD OF MEDICINE AG	6
BURGBAD AG	5	FIELMANN AG	16	KHD HUMBOLDT WEDAG INTL(DT)	9	NYNOMIC AG	10	SOFTSHIP AG	5	YOC AG	2
CAATOOSEE AG	8	FIRST SENSOR AG	16	KION GROUP GMBH	3	OBERSTDORFER BERGBAHN AG	2	SOFTWARE AG	16	YOUR FAMILY ENTERTAINMENT AG	16
CANCOM SE	16	FORMYCON AG	2	KLASSIK RADIO AG	12	ODEON FILM AG	16	SOLAR MILLENNIUM AG	1	ZALANDO SE	5
CARL ZEISS MEDITEC AG	16	FORST EBNATH AG	9	KLOCKNER & CO SE	15	OHB SE	15	SOLAR-FABRIK AG	7	ZAPF CREATION AG	5
CCR LOGISTICS SYSTEMS AG	10	FORTEC ELEKTRONIK VERTRIEBS	16	KLOECKNER-WERKE AG	5	OLYMPIA FLEXGROUP AG	2	SOLARPARC AG	6	ZEAG ENERGIE AG	9
CDV SOFTWARE ENTERTAINMENT	1	FRANCOTYP POSTALIA HLDG AG	10	KNORR-BREMSE AKTIE	3	ONVISTA AG	1	SOLARWORLD AG	8	ZEAL NETWORK SE	12
CECONOMY AG	16	FRAPORT AG	16	KOEHLER & KRENZER FASHION AG	2	ORBIS AG	15	SOLON SE	1	ZHONGDE WASTE TECHNOLOGY AG	7
CELANESE AG	1	FREENET AG	16	KOENIG & BAUER AG	16	OSRAM LICHT AG	5	SOLUTIANCE AG	8	ZOOPLUS SE	11
CENIT AG	16	FRESENIUS MEDICAL CARE AG&CO	16	KOFLER ENERGIES POWER AG	3	OTRS AG	5	SPLENDID MEDIEN AG	16		

Figure 15: List of firms included in the analysis with an ESG score

Company Name	# of ESG Scores	Company Name	# of ESG Scores	Company Name	# of ESG Scores
11880 SOLUTIONS AG	1	FIELMANN AG	13	NEXUS AG	1
2G ENERGY AG	1	FIRST SENSOR AG	1	NORDEX SE	3
ABO WIND AG	1	FRANCOTYP POSTALIA HLDG AG	2	NORMA GROUP SE	3
ADESSO SE	2	FRAPORT AG	16	OHB SE	3
ADIDAS AG	16	FREENET AG	10	OSRAM LICHT AG	5
ADVA AG OPTICAL NETWORKING	3	FRESENIUS MEDICAL CARE AG&CO	16	PARAGON AG	1
AHLERS AG	1	FRESENIUS SE & CO KGAA	14	PFEIFFER VACUUM TECHNOLOGY	3
AIXTRON SE	13	FROSTA AG	1	PNE AG	2
ALL FOR ONE GROUP SE	2	FUCHS PETROLUB SE	11	PORSCHE AUTOMOBIL HOLDING S	5
ALLGEIER SE	1	GEA GROUP AG	16	PROGRESS-WERK OBERKIRCH AG	1
ALTANA AG	5	GERRESHEIMER GROUP	8	PROSIEBENSAT.1 MEDIA SE	16
AMADEUS FIRE AG	3	GESCO AG	2	PSI SOFTWARE AG	1
ARCANDOR AG	4	GFT TECHNOLOGIES AG	3	PUMA SE	16
AS CREATION TAPETEN AG	1	GK SOFTWARE SE	1	PVA TEPLA AG	1
AUDI AG	1	GLOBAL PVQ SE	2	Q BEYOND AG	1
AUMANN AG	2	GRAMMER AG	1	R STAHL AG	1
AURUBIS AG	14	H&R GMBH & CO KGAA	3	RATIONAL AG	4
AXEL SPRINGER SE	11	HAMBURGER HAFEN UND LOGISTI	14	RHEINMETALL AG	16
BASF SE	16	HAPAG-LLOYD AG	4	RHOEN-KLINIKUM AG	16
BASLER (VISION TECHNOLOGIES)	3	HAWESKO HOLDING AG	1	RIB SOFTWARE SE	3
BAUER AG	1	HEIDELBERGCEMENT AG	16	RWE AG	16
BAYER AG	16	HEIDELBERGER DRUCKMASCHINEN	16	SALZGITTER AG	16
BAYER MOTOREN WERKE AG	16	HELLA GMBH & CO. KGAA	3	SAP SE	16
BAYER SCHERING PHARMA AG	3	HELLOFRESH SE	1	SARTORIUS AG	6
BAYWA AG	3	HENKEL AG & CO KGAA	16	SCHAEFFLER AG	1
BECHTLE AG	4	HOCHTIEF AG	16	SCHALTBAU HOLDING AG	1
BEIERSDORF AG	16	HOFTEX GROUP AG	1	SCHWEIZER ELECTRONIC AG	1
BERENTZEN-GRUPPE AG	1	HOME24 SE	1	SCOUT24 SE	1
BERTRANDT AG	3	HORNBACH HOLDING AG & CO	2	SECUNET SECURITY NETWORKS A(	1
BET-AT-HOME COM AG	3	HORNBACH-BAUMARKT AG	2	SGL CARBON SE	16
BIJOU BRIGITTE MOD ACCESS AG	1	HUGO BOSS AG	10	SHW AG	1
BILFINGER SE	16	INDUS HOLDING AG	3	SIEMENS AG	16
BIOTEST AG	3	INFINEON TECHNOLOGIES AG	16	SILTRONIC AG	3
BLG-BREMER LAGERHAUS-GESELLS	1	INIT INNOVATION TRAFFIC SE	1	SIMONA KUNSTSTOFFWERKE AG	1
BORUSSIA DORTMUND GMBH & C(	2	INTICOM SYSTEMS AG	1	SIXT SE	4
BRENNTAG SE	8	ISRA VISION AG	2	SKY DEUTSCHLAND AG	5
CANCOM SE	3	IVU TRAFFIC TECHNOLOGIES AG	1	SLM SOLUTIONS GMBH	2
CARL ZEISS MEDITEC AG	4	JENOPTIK AG	3	SMA SOLAR TECHNOLOGY AG	3
CECONOMY AG	16	JOST AG	3	SNP SCHNEIDER-NEUREITHER & P	1
CENIT AG	1	JUNGHEINRICH AG	3	SOFTWARE AG	13
CENTROTHERM INTERNATIONAL A	2	K&S AG	16	SOLARWORLD AG	8
CEWE STIFTUNG & CO KGAA	3	KAP AG	1	STADA ARZNEIMITTEL AG	15
COMPUGROUP MEDICAL SE & CO	3	KHD HUMBOLDT WEDAG INTL(DT)	1	STEICO AG	1
CONTINENTAL AG	16	KION GROUP GMBH	3	STO SE & CO KGAA	3
COVESTRO AG	2	KNORR-BREMSE AKTIE	3	STRATEC SE	3
CROPENERGIES AG	1	KOENIG & BAUER AG	3	STROEER SE & CO KGAA	3
CTS EVENTIM AG & CO KGAA	4	KPS AG	1	SUEDZUCKER AG	16
DATA MODUL AG	1	KRONES AG	4	SUESS MICROTEC SE	1
DATAGROUP SE	1	KSB SE & CO KGAA	1	SURTECO SE	3
DEGUSSA AG	1	KUKA AG	1	SYMRISE AG	11
DELIVERY HERO AG	2	KWS SAAT SE & CO KGAA	3	SYZYGY AG	1
DERMAPHARM HOLDING	1	LANXESS AG	11	TAKKT AG	2
DEUFOL SE	1	LEIFHEIT AG	1	TECHNOTRANS AG	1
DEUTSCHE LUFTHANSA AG	16	LEONI AG	13	TELEFONICA DEUTSCHLAND	6
DEUTSCHE POST AG	16	LINDE AG	13	TEREX MATERIAL HANDLING	4
DEUTSCHE TELEKOM	16	LPKF-LASER & ELECTRONICS AG	2	THYSSENKRUPP AG	16
DEUTZ AG	3	MAN SE	16	TOGNUM AG	2
DIEBOLD NIXDORF AG	8	MANZ AG	1	TUI AG	15
DMG MORI AG	4	MASCHINENFABRIK BERTHOLD	1	UNIPER SE	2
DOUGLAS HOLDING AG	8	MASTERFLEX SE	1	UNITED INTERNET AG	16
DR HOENLE AG	1	MAX AUTOMATION	1	USU SOFTWARE AG	1
DRAEGERWERK AG	3	MCKESSON EUROPE AG	10	UZIN UTZ AG	1
DUERR AG	7	MEDICLIN AG	1	VA-Q-TEC AG	1
E.ON SE	11	MENSCH & MASCHINE SOFTWARE	1	VERBIO VEREINIGTE BIOENERGIE	3
ECKERT & ZIEGLER AG	2	MERCEDES-BENZ GROUP AG	16	VILLEROY & BOCH AG	1
EDDING AG	1	MERCK KOMMANDITGESELLSCHAI	15	VISCOM AG	1
EINHELL GERMANY AG	1	METRO AG	1	VOLKSWAGEN AG	16
ELMOS SEMICONDUCTOR SE	3	MORPHOSYS AG	7	VOSSLOH AG	4
ELRINGKLINGER AG	13	MSG LIFE AG	1	WACKER CHEMIE AG	15
ENBW ENERGIE BADEN	1	MTU AERO ENGINES AG	11	WACKER NEUSON SE	3
ENVITEC BIOGAS AG	1	MUEHLHAN AG	1	WASHTEC AG	3
EPCOS AG	4	MVV ENERGIE AG	13	WIRECARD AG	8
EUROKAI KGAA	2	NABALTEC AG	1	ZALANDO SE	5
EVONIK INDUSTRIES AG	8	NEMETSCHEK SE	4	ZOOPLUS SE	3
EVOTEC SE	4	NEW WORK SE	3		

9.2 Appendix - Quality prices

Table 23: Cross-section regressions Profitability Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z prof	0.127***	0.149***	0.177***	0.105**	0.167***	0.171***	0.223***	0.224***
	(0.041)	(0.038)	(0.040)	(0.043)	(0.038)	(0.034)	(0.038)	(0.039)
Cons	0.700***	0.745***	0.534***	0.089**	0.398***	0.538***	0.403***	0.443***
	(0.041)	(0.038)	(0.040)	(0.043)	(0.037)	(0.034)	(0.038)	(0.039)
N	381	407	394	383	393	415	435	420
Adj R^2	0.023	0.034	0.046	0.012	0.046	0.056	0.070	0.072

Note: *p<0.1; **p<0.05; ***p<0.01

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Table 24: Cross-section regressions Profitability Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z prof	0.168***	0.158***	0.194***	0.265***	0.233***	0.293***	0.258***	0.116**	0.189***
	(0.041)	(0.043)	(0.043)	(0.043)	(0.044)	(0.045)	(0.051)	(0.054)	(0.011)
Cons	0.627***	0.687***	0.654***	0.807***	0.838***	0.699***	0.534***	0.940***	0.595***
	(0.040)	(0.043)	(0.043)	(0.043)	(0.044)	(0.045)	(0.051)	(0.054)	(0.011)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.038	0.032	0.052	0.092	0.071	0.107	0.065	0.010	0.047

Note: *p<0.1; **p<0.05; ***p<0.01

Table 25: Cross-section regressions Growth Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z growth	0.176***	0.235***	0.159***	0.140***	0.142***	0.214***	0.207***	0.133***
	(0.040)	(0.037)	(0.040)	(0.043)	(0.038)	(0.033)	(0.039)	(0.040)
Cons	0.700***	0.745***	0.534***	0.089**	0.398***	0.538***	0.403***	0.443***
	(0.040)	(0.037)	(0.040)	(0.043)	(0.038)	(0.033)	(0.039)	(0.040)
N	381	407	394	383	393	415	435	420
Adj R^2	0.046	0.088	0.037	0.024	0.033	0.088	0.060	0.024

Note: *p<0.1; **p<0.05; ***p<0.01

Table 26: Cross-section regressions Growth Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z growth	0.184***	0.221***	0.197***	0.271***	0.300***	0.280***	0.287***	0.238***	0.209***
	(0.040)	(0.043)	(0.043)	(0.043)	(0.043)	(0.045)	(0.050)	(0.053)	(0.011)
Cons	0.627***	0.687***	0.654***	0.807***	0.838***	0.699***	0.534***	0.940***	0.595***
	(0.040)	(0.043)	(0.043)	(0.043)	(0.043)	(0.045)	(0.050)	(0.052)	(0.011)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.047	0.065	0.053	0.096	0.119	0.097	0.081	0.054	0.058

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 27: Cross-section regressions Safety Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z safety	0.114***	0.089**	0.134***	0.163***	0.135***	0.147***	0.171***	0.170***
	(0.041)	(0.039)	(0.040)	(0.043)	(0.038)	(0.034)	(0.039)	(0.039)
Cons	0.700***	0.745***	0.534***	0.089**	0.398***	0.538***	0.403***	0.443***
	(0.041)	(0.039)	(0.040)	(0.043)	(0.038)	(0.034)	(0.039)	(0.039)
N	381	407	394	383	393	415	435	420
Adj R^2	0.018	0.011	0.025	0.034	0.029	0.040	0.040	0.040

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 28: Cross-section regressions Safety Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z safety	0.128***	0.072	0.140***	0.102**	0.165***	0.163***	0.114**	0.074	0.131***
	(0.041)	(0.044)	(0.043)	(0.045)	(0.045)	(0.047)	(0.052)	(0.054)	(0.011)
Cons	0.627***	0.687***	0.654***	0.807***	0.838***	0.699***	0.534***	0.940***	0.595***
	(0.041)	(0.044)	(0.043)	(0.045)	(0.045)	(0.047)	(0.052)	(0.054)	(0.011)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.021	0.004	0.026	0.011	0.034	0.031	0.010	0.003	0.023

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 29: Cross-section regressions ESG Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z ESG	−0.089	−0.079	−0.022	−0.005	−0.098	−0.151*	−0.215**	−0.259**
	(0.108)	(0.084)	(0.098)	(0.103)	(0.087)	(0.077)	(0.094)	(0.102)
Cons	0.920***	0.955***	0.696***	0.235**	0.592***	0.718***	0.576***	0.672***
	(0.107)	(0.083)	(0.097)	(0.103)	(0.086)	(0.076)	(0.093)	(0.101)
N	49	49	52	57	59	63	65	64
Adj R^2	−0.007	−0.002	−0.019	−0.018	0.005	0.044	0.062	0.079

Note: *p<0.1; **p<0.05; ***p<0.01

Table 30: Cross-section regressions ESG Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z ESG	−0.194**	−0.141*	−0.087	−0.012	−0.153*	−0.190**	−0.133*	0.027	−0.105***
	(0.088)	(0.083)	(0.079)	(0.080)	(0.081)	(0.078)	(0.079)	(0.064)	(0.023)
Cons	0.854***	0.919***	0.763***	0.911***	0.991***	0.849***	0.558***	0.953***	0.775***
	(0.087)	(0.083)	(0.078)	(0.080)	(0.080)	(0.077)	(0.079)	(0.064)	(0.022)
N	64	66	66	67	78	118	139	195	1,251
Adj R^2	0.058	0.028	0.003	−0.015	0.033	0.041	0.013	−0.004	0.016

Note: *p<0.1; **p<0.05; ***p<0.01

Table 31: Cross-section regressions Quality and Dummy ESG Part 1

	log_firm_value							
	2006	2007	2008	2009	2010	2011	2012	2013
z quality	0.186***	0.217***	0.206***	0.167***	0.191***	0.217***	0.240***	0.214***
	(0.041)	(0.038)	(0.039)	(0.043)	(0.037)	(0.033)	(0.038)	(0.039)
DV ESG	0.139	0.149	0.111	0.143	0.269***	0.165*	0.162	0.256**
	(0.122)	(0.115)	(0.116)	(0.121)	(0.104)	(0.092)	(0.107)	(0.108)
Cons	0.682***	0.727***	0.519***	0.068	0.358***	0.513***	0.378***	0.404***
	(0.043)	(0.040)	(0.042)	(0.046)	(0.040)	(0.036)	(0.041)	(0.042)
N	381	407	394	383	393	415	435	420
Adj R^2	0.058	0.081	0.066	0.038	0.070	0.100	0.087	0.077

Note: *p<0.1; **p<0.05; ***p<0.01

Table 32: Cross-section regressions Quality and Dummy ESG Part 2

	log_firm_value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z quality	0.201***	0.182***	0.220***	0.274***	0.293***	0.296***	0.273***	0.169***	0.218***
	(0.040)	(0.043)	(0.043)	(0.043)	(0.043)	(0.046)	(0.051)	(0.054)	(0.011)
DV ESG	0.251**	0.236**	0.101	0.139	0.141	0.080	−0.037	−0.007	0.183***
	(0.110)	(0.113)	(0.110)	(0.111)	(0.104)	(0.097)	(0.105)	(0.108)	(0.026)
Cons	0.588***	0.646***	0.636***	0.781***	0.807***	0.672***	0.548***	0.944***	0.558***
	(0.043)	(0.047)	(0.047)	(0.048)	(0.049)	(0.055)	(0.065)	(0.081)	(0.012)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.067	0.056	0.068	0.099	0.119	0.115	0.070	0.023	0.074
Note:									*p<0.1; **p<0.05; ***p<0.01

Table 33: Cross-section regressions Quality Small Sample Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z quality	0.373***	0.370***	0.316***	0.301***	0.368***	0.273***	0.327***	0.271***
	(0.094)	(0.066)	(0.087)	(0.095)	(0.073)	(0.071)	(0.089)	(0.102)
Cons	0.920***	0.955***	0.696***	0.235**	0.592***	0.718***	0.576***	0.672***
	(0.093)	(0.065)	(0.086)	(0.094)	(0.073)	(0.071)	(0.088)	(0.101)
N	49	49	52	57	59	63	65	64
Adj R^2	0.236	0.390	0.192	0.138	0.294	0.180	0.164	0.088
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 34: Cross-section regressions Quality Small Sample Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z quality	0.264***	0.243***	0.317***	0.319***	0.399***	0.545***	0.524***	0.306***	0.360***
	(0.085)	(0.080)	(0.069)	(0.070)	(0.069)	(0.062)	(0.066)	(0.061)	(0.020)
Cons	0.854***	0.919***	0.763***	0.911***	0.991***	0.849***	0.558***	0.953***	0.775***
	(0.084)	(0.079)	(0.069)	(0.069)	(0.068)	(0.061)	(0.066)	(0.060)	(0.020)
N	64	66	66	67	78	118	139	195	1,251
Adj R^2	0.120	0.113	0.235	0.231	0.298	0.398	0.308	0.112	0.200
Note:									*p<0.1; **p<0.05; ***p<0.01

Table 35: Cross-section regressions Quality - control for size Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z quality	0.130***	0.170***	0.154***	0.128***	0.161***	0.191***	0.208***	0.175***
	(0.042)	(0.038)	(0.040)	(0.043)	(0.037)	(0.034)	(0.039)	(0.040)
z size	0.170***	0.192***	0.191***	0.188***	0.159***	0.108***	0.132***	0.149***
	(0.042)	(0.038)	(0.040)	(0.043)	(0.037)	(0.034)	(0.039)	(0.040)
Cons	0.700***	0.745***	0.534***	0.089**	0.398***	0.538***	0.403***	0.443***
	(0.039)	(0.036)	(0.038)	(0.042)	(0.036)	(0.033)	(0.038)	(0.038)
N	381	407	394	383	393	415	435	420
Adj R^2	0.093	0.133	0.116	0.081	0.097	0.114	0.106	0.094

Note: *p<0.1; **p<0.05; ***p<0.01

Table 36: Cross-section regressions Quality - control for size Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z quality	0.165***	0.131***	0.187***	0.240***	0.267***	0.268***	0.240***	0.128**	0.182***
	(0.040)	(0.045)	(0.044)	(0.045)	(0.045)	(0.047)	(0.052)	(0.053)	(0.011)
z size	0.171***	0.181***	0.122***	0.118***	0.108**	0.105**	0.118**	0.205***	0.152***
	(0.040)	(0.045)	(0.044)	(0.045)	(0.045)	(0.047)	(0.052)	(0.053)	(0.011)
Cons	0.627***	0.687***	0.654***	0.807***	0.838***	0.699***	0.534***	0.940***	0.595***
	(0.039)	(0.042)	(0.042)	(0.043)	(0.043)	(0.044)	(0.050)	(0.052)	(0.011)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.095	0.085	0.086	0.113	0.129	0.125	0.083	0.063	0.095

Note: *p<0.1; **p<0.05; ***p<0.01

Table 37: Cross-section regressions Quality - control for dividends Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z quality	0.235***	0.253***	0.241***	0.194***	0.199***	0.245***	0.259***	0.227***
	(0.042)	(0.039)	(0.041)	(0.045)	(0.040)	(0.036)	(0.041)	(0.041)
DV Div	−0.232***	−0.183**	−0.183**	−0.162*	−0.089	−0.133*	−0.083	−0.074
	(0.085)	(0.079)	(0.082)	(0.090)	(0.081)	(0.071)	(0.083)	(0.082)
Cons	0.799***	0.826***	0.623***	0.162***	0.434***	0.598***	0.439***	0.476***
	(0.054)	(0.051)	(0.056)	(0.059)	(0.049)	(0.046)	(0.053)	(0.053)
N	381	407	394	383	393	415	435	420
Adj R^2	0.073	0.089	0.076	0.043	0.056	0.100	0.084	0.066

Note: *p<0.1; **p<0.05; ***p<0.01

Table 38: Cross-section regressions Quality - control for dividends Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z quality	0.208***	0.196***	0.232***	0.300***	0.341***	0.344***	0.283***	0.209***	0.243***
	(0.043)	(0.046)	(0.045)	(0.046)	(0.045)	(0.048)	(0.053)	(0.058)	(0.011)
DV Div	−0.024	−0.032	−0.063	−0.154*	−0.264***	−0.206**	−0.096	−0.205*	−0.116***
	(0.085)	(0.092)	(0.090)	(0.092)	(0.091)	(0.096)	(0.109)	(0.117)	(0.023)
Cons	0.638***	0.703***	0.685***	0.888***	0.986***	0.807***	0.568***	1.028***	0.648***
	(0.056)	(0.062)	(0.061)	(0.065)	(0.067)	(0.067)	(0.064)	(0.073)	(0.015)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.055	0.045	0.067	0.102	0.136	0.124	0.071	0.031	0.070
Note:									*p<0.1; **p<0.05; ***p<0.01

Table 39: Cross-section regressions Quality - control for size and dividends Part 1

	log firm value							
	2006	2007	2008	2009	2010	2011	2012	2013
z quality	0.169***	0.214***	0.198***	0.167***	0.202***	0.224***	0.241***	0.199***
	(0.042)	(0.038)	(0.040)	(0.043)	(0.038)	(0.035)	(0.040)	(0.040)
z size	0.267***	0.273***	0.290***	0.273***	0.219***	0.158***	0.190***	0.203***
	(0.045)	(0.040)	(0.043)	(0.047)	(0.040)	(0.037)	(0.044)	(0.044)
DV Div	−0.455***	−0.410***	−0.448***	−0.403***	−0.293***	−0.261***	−0.266***	−0.253***
	(0.090)	(0.082)	(0.088)	(0.095)	(0.087)	(0.076)	(0.091)	(0.089)
Cons	0.894***	0.926***	0.753***	0.269***	0.515***	0.655***	0.519***	0.555***
	(0.054)	(0.050)	(0.057)	(0.059)	(0.050)	(0.047)	(0.055)	(0.055)
N	381	407	394	383	393	415	435	420
Adj R^2	0.149	0.182	0.169	0.120	0.120	0.137	0.121	0.109
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 40: Cross-section regressions Quality - control for size and dividends Part 2

	log firm value								
	2014	2015	2016	2017	2018	2019	2020	2021	Total
z quality	0.191***	0.158***	0.209***	0.277***	0.311***	0.310***	0.256***	0.198***	0.216***
	(0.041)	(0.046)	(0.045)	(0.045)	(0.045)	(0.048)	(0.053)	(0.056)	(0.011)
z size	0.224***	0.232***	0.172***	0.190***	0.182***	0.171***	0.149***	0.281***	0.213***
	(0.045)	(0.049)	(0.049)	(0.049)	(0.047)	(0.051)	(0.055)	(0.057)	(0.012)
DV Div	−0.238**	−0.237**	−0.222**	−0.329***	−0.403***	−0.341***	−0.198*	−0.433***	−0.298***
	(0.093)	(0.100)	(0.099)	(0.101)	(0.097)	(0.103)	(0.115)	(0.122)	(0.024)
Cons	0.737***	0.803***	0.763***	0.979***	1.063***	0.877***	0.605***	1.126***	0.732***
	(0.058)	(0.064)	(0.064)	(0.068)	(0.068)	(0.069)	(0.065)	(0.073)	(0.015)
N	407	374	359	361	348	351	355	346	6,129
Adj R^2	0.108	0.097	0.096	0.136	0.169	0.150	0.088	0.094	0.117
Note:									*p<0.1; **p<0.05; ***p<0.01

9.3 Appendix - Investment approach

Table 41: CAPM - value weights

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
MKT	0.883***	0.793***	0.766***	0.772***	0.734***	0.888***	0.769***	−0.149**	−0.119**
	(0.058)	(0.049)	(0.047)	(0.043)	(0.041)	(0.052)	(0.040)	(0.057)	(0.050)
α	0.001	−0.003	−0.001	0.002	0.002	−0.002	0.003	0.001	0.005*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
N	188	188	188	188	188	188	188	188	188
Adj R^2	0.555	0.582	0.588	0.637	0.637	0.613	0.667	0.030	0.024
Note:									*p<0.1; **p<0.05; ***p<0.01

Table 42: Fama-French 5 factor model - value weights

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
MKT	0.880***	0.778***	0.724***	0.787***	0.754***	0.876***	0.808***	−0.126*	−0.068
	(0.078)	(0.066)	(0.063)	(0.057)	(0.052)	(0.070)	(0.051)	(0.074)	(0.065)
SMB	0.338*	−0.022	−0.211	−0.250*	−0.158	0.083	−0.194	−0.496***	−0.277*
	(0.182)	(0.154)	(0.146)	(0.132)	(0.121)	(0.164)	(0.119)	(0.172)	(0.151)
HML	−0.074	0.338*	0.377**	0.049	0.006	0.162	−0.049	0.080	−0.211
	(0.235)	(0.199)	(0.189)	(0.171)	(0.156)	(0.212)	(0.154)	(0.223)	(0.195)
RMW	−0.154	0.570**	0.506*	0.325	0.402*	0.225	0.385*	0.556*	0.160
	(0.328)	(0.278)	(0.264)	(0.238)	(0.218)	(0.295)	(0.215)	(0.311)	(0.272)
CMA	0.056	0.176	−0.169	−0.250	−0.471**	0.121	−0.324	−0.527*	−0.445*
	(0.303)	(0.257)	(0.244)	(0.220)	(0.201)	(0.273)	(0.199)	(0.287)	(0.252)
α	0.001	−0.005	−0.002	0.001	−0.00002	−0.002	0.001	−0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
N	188	188	188	188	188	188	188	188	188
Adj R^2	0.555	0.587	0.595	0.649	0.676	0.608	0.699	0.119	0.108

Note: *p<0.1; **p<0.05; ***p<0.01

Table 43: CAPM - equal weights

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
MKT	0.587***	0.649***	0.618***	0.614***	0.621***	0.613***	0.613***	0.034	0.0005
	(0.039)	(0.035)	(0.032)	(0.033)	(0.032)	(0.035)	(0.031)	(0.032)	(0.026)
α	0.0004	0.003	0.004**	0.005***	0.005***	0.001	0.006***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
N	188	188	188	188	188	188	188	188	188
Adj R^2	0.545	0.650	0.672	0.651	0.670	0.614	0.670	0.001	−0.005

Note: *p<0.1; **p<0.05; ***p<0.01

Table 44: Fama-French 5 factor model - equal weights

	P1	P2	P3	P4	P5	PJ30	PQ30	TMB	TMB30
MKT	0.575***	0.600***	0.549***	0.611***	0.615***	0.575***	0.618***	0.040	0.043
	(0.049)	(0.043)	(0.040)	(0.042)	(0.039)	(0.044)	(0.039)	(0.041)	(0.033)
SMB	0.598***	0.566***	0.428***	0.448***	0.415***	0.613***	0.460***	−0.183*	−0.153**
	(0.115)	(0.101)	(0.092)	(0.097)	(0.091)	(0.102)	(0.090)	(0.096)	(0.077)
HML	−0.103	0.189	0.310**	0.079	0.017	0.061	0.015	0.119	−0.046
	(0.149)	(0.130)	(0.120)	(0.125)	(0.118)	(0.132)	(0.116)	(0.124)	(0.099)
RMW	−0.240	0.171	0.267	0.324*	0.231	−0.066	0.288*	0.471***	0.355**
	(0.208)	(0.182)	(0.167)	(0.175)	(0.164)	(0.184)	(0.162)	(0.173)	(0.138)
CMA	0.017	−0.163	−0.263*	−0.104	−0.321**	−0.047	−0.179	−0.338**	−0.131
	(0.192)	(0.168)	(0.154)	(0.162)	(0.152)	(0.170)	(0.150)	(0.160)	(0.128)
α	0.0005	0.002	0.003	0.003	0.004**	0.0003	0.004**	0.003*	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
N	188	188	188	188	188	188	188	188	188
Adj R^2	0.605	0.705	0.717	0.694	0.730	0.680	0.729	0.106	0.127

Note: *p<0.1; **p<0.05; ***p<0.01

Table 45: CAPM - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.745***	0.650***	−0.096***	0.854***	0.753***	−0.101**	−0.098***
	(0.041)	(0.039)	(0.034)	(0.048)	(0.042)	(0.047)	(0.032)
α	−0.001	0.005**	0.006***	−0.002	0.002	0.004	0.005***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.637	0.594	0.036	0.624	0.629	0.019	0.043

Note: *p<0.1; **p<0.05; ***p<0.01

Table 46: Fama-French 5 factor model - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.712***	0.704***	−0.008	0.799***	0.772***	−0.027	−0.018
	(0.051)	(0.048)	(0.044)	(0.065)	(0.054)	(0.061)	(0.041)
SMB	0.693***	0.622***	−0.071	−0.052	−0.194	−0.143	−0.107
	(0.120)	(0.113)	(0.103)	(0.153)	(0.126)	(0.142)	(0.095)
HML	0.152	−0.206	−0.358***	0.398**	0.017	−0.381**	−0.370***
	(0.155)	(0.146)	(0.133)	(0.197)	(0.163)	(0.184)	(0.122)
RMW	0.188	0.177	−0.011	0.444	0.420*	−0.024	−0.018
	(0.216)	(0.204)	(0.185)	(0.275)	(0.228)	(0.256)	(0.171)
CMA	0.005	0.088	0.083	−0.134	−0.480**	−0.347	−0.132
	(0.199)	(0.188)	(0.171)	(0.254)	(0.211)	(0.237)	(0.158)
α	−0.002	0.003	0.005***	−0.003	−0.0003	0.003	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.692	0.662	0.100	0.625	0.667	0.114	0.174

Note: *p<0.1; **p<0.05; ***p<0.01

Table 47: CAPM - size sorted 90/10

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.740***	0.675***	−0.065*	0.878***	0.757***	−0.122**	−0.093***
	(0.040)	(0.038)	(0.036)	(0.051)	(0.045)	(0.051)	(0.034)
α	−0.0002	0.005**	0.006***	−0.003	0.001	0.004	0.005**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.646	0.627	0.012	0.611	0.604	0.024	0.033

Note: *p<0.1; **p<0.05; ***p<0.01

Table 48: Fama-French 5 factor model - size sorted 90/10

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.788***	0.740***	−0.048	0.830***	0.771***	−0.059	−0.054
	(0.051)	(0.047)	(0.044)	(0.069)	(0.057)	(0.067)	(0.042)
SMB	0.589***	0.458***	−0.132	−0.122	−0.271**	−0.149	−0.140
	(0.118)	(0.108)	(0.103)	(0.162)	(0.134)	(0.156)	(0.098)
HML	−0.306**	−0.214	0.092	0.332	0.052	−0.280	−0.094
	(0.153)	(0.140)	(0.133)	(0.209)	(0.173)	(0.202)	(0.126)
RMW	−0.301	0.308	0.609***	0.354	0.449*	0.095	0.352**
	(0.214)	(0.196)	(0.185)	(0.292)	(0.242)	(0.281)	(0.176)
CMA	0.431**	−0.085	−0.516***	−0.160	−0.498**	−0.338	−0.427***
	(0.197)	(0.181)	(0.171)	(0.270)	(0.223)	(0.260)	(0.163)
α	−0.0004	0.002	0.003	−0.004	−0.001	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.689	0.696	0.202	0.610	0.643	0.087	0.209

Note: *p<0.1; **p<0.05; ***p<0.01

Table 49: CAPM - size sorted Median

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.556***	0.535***	−0.021	0.841***	0.771***	−0.070	−0.045
	(0.042)	(0.036)	(0.039)	(0.045)	(0.041)	(0.046)	(0.032)
α	−0.002	0.006***	0.009***	−0.002	0.002	0.005*	0.007***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.485	0.541	−0.004	0.646	0.653	0.007	0.005

Note: *p<0.1; **p<0.05; ***p<0.01

Table 50: Fama-French 3 factor model - size sorted Median

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.516***	0.545***	0.029	0.819***	0.858***	0.039	0.034
	(0.046)	(0.039)	(0.045)	(0.053)	(0.046)	(0.050)	(0.035)
SMB	0.475***	0.543***	0.068	0.077	−0.131	−0.208	−0.070
	(0.121)	(0.101)	(0.116)	(0.137)	(0.120)	(0.131)	(0.091)
HML	0.124	−0.097	−0.222**	0.088	−0.358***	−0.446***	−0.334***
	(0.098)	(0.081)	(0.094)	(0.111)	(0.096)	(0.106)	(0.074)
α	−0.003	0.005***	0.008***	−0.002	0.001	0.003	0.006***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.522	0.602	0.017	0.644	0.675	0.095	0.097

Note: *p<0.1; **p<0.05; ***p<0.01

Table 51: Fama-French 5 factor model - size sorted Median

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.546***	0.514***	−0.032	0.821***	0.798***	−0.024	−0.028
	(0.055)	(0.045)	(0.052)	(0.062)	(0.053)	(0.059)	(0.040)
SMB	0.495***	0.515***	0.020	0.106	−0.181	−0.287**	−0.133
	(0.127)	(0.106)	(0.120)	(0.144)	(0.124)	(0.136)	(0.094)
HML	−0.050	0.052	0.101	0.226	−0.053	−0.278	−0.089
	(0.164)	(0.137)	(0.156)	(0.186)	(0.160)	(0.176)	(0.122)
RMW	−0.202	0.133	0.335	0.338	0.299	−0.039	0.148
	(0.229)	(0.191)	(0.217)	(0.260)	(0.224)	(0.246)	(0.170)
CMA	0.195	−0.217	−0.412**	0.060	−0.411**	−0.470**	−0.441***
	(0.212)	(0.176)	(0.200)	(0.240)	(0.207)	(0.227)	(0.157)
α	−0.002	0.005**	0.007***	−0.003	0.001	0.004	0.006***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
N	188	188	188	188	188	188	188
Adj R^2	0.522	0.603	0.044	0.644	0.683	0.106	0.131

Note: *p<0.1; **p<0.05; ***p<0.01

Table 52: CAPM - Industrials size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.876***	0.803***	−0.073	0.942***	0.820***	−0.123	−0.098**
	(0.057)	(0.050)	(0.054)	(0.065)	(0.058)	(0.077)	(0.048)
α	0.001	0.004	0.003	0.0001	0.002	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
N	188	188	188	188	188	188	188
Adj R^2	0.559	0.578	0.004	0.527	0.512	0.008	0.017

Note: *p<0.1; **p<0.05; ***p<0.01

Table 53: Fama-French 3 factor model Industrials - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.840***	0.832***	−0.008	0.973***	0.874***	−0.099	−0.053
	(0.064)	(0.056)	(0.062)	(0.075)	(0.067)	(0.089)	(0.055)
SMB	0.547***	0.480***	−0.068	−0.026	0.217	0.243	0.088
	(0.167)	(0.146)	(0.163)	(0.197)	(0.174)	(0.234)	(0.143)
HML	0.098	−0.175	−0.273**	−0.128	−0.253*	−0.125	−0.199*
	(0.135)	(0.118)	(0.131)	(0.159)	(0.141)	(0.188)	(0.115)
α	0.0001	0.002	0.002	−0.0003	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
N	188	188	188	188	188	188	188
Adj R^2	0.580	0.602	0.017	0.524	0.520	0.006	0.025

Note: *p<0.1; **p<0.05; ***p<0.01

Table 54: Fama-French 5 factor model Industrials - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKT	0.809^{***}	0.804^{***}	-0.005	0.996^{***}	0.867^{***}	-0.129	-0.067
	(0.075)	(0.065)	(0.073)	(0.089)	(0.079)	(0.106)	(0.064)
SMB	0.545^{***}	0.484^{***}	-0.061	0.003	0.211	0.208	0.074
	(0.175)	(0.153)	(0.171)	(0.207)	(0.184)	(0.246)	(0.150)
HML	0.388^{*}	0.128	-0.260	-0.184	-0.216	-0.032	-0.146
	(0.226)	(0.197)	(0.221)	(0.268)	(0.237)	(0.318)	(0.194)
RMW	0.461	0.509^{*}	0.048	0.025	0.040	0.015	0.031
	(0.315)	(0.275)	(0.309)	(0.374)	(0.331)	(0.444)	(0.271)
CMA	-0.176	-0.152	0.024	0.173	-0.047	-0.219	-0.098
	(0.291)	(0.254)	(0.285)	(0.345)	(0.306)	(0.410)	(0.250)
α	-0.001	0.001	0.002	-0.001	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
N	188	188	188	188	188	188	188
Adj R^2	0.581	0.607	0.007	0.519	0.515	-0.004	0.015

Note: *p<0.1; **p<0.05; ***p<0.01

Table 55: CAPM IT - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.826^{***}	0.735^{***}	-0.091	0.999^{***}	0.775^{***}	-0.224^{**}	-0.157^{**}
	(0.068)	(0.052)	(0.066)	(0.087)	(0.084)	(0.108)	(0.067)
α	0.001	0.008^{***}	0.007^{*}	0.002	0.004	0.001	0.004
	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
N	188	188	188	188	188	188	188
Adj R^2	0.438	0.512	0.005	0.412	0.310	0.017	0.024

Note: *p<0.1; **p<0.05; ***p<0.01

Table 56: Fama-French 3 factor model IT - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.752***	0.797***	0.045	0.967***	0.932***	−0.035	0.005
	(0.074)	(0.056)	(0.074)	(0.100)	(0.095)	(0.122)	(0.074)
SMB	0.945***	0.704***	−0.241	0.403	0.039	−0.364	−0.303
	(0.194)	(0.146)	(0.194)	(0.262)	(0.247)	(0.319)	(0.193)
HML	0.222	−0.337***	−0.559***	0.097	−0.673***	−0.770***	−0.665***
	(0.156)	(0.118)	(0.156)	(0.211)	(0.199)	(0.257)	(0.155)
α	0.001	0.006**	0.005	0.002	0.002	−0.001	0.002
	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
N	188	188	188	188	188	188	188
Adj R^2	0.501	0.581	0.065	0.413	0.344	0.058	0.111

Note: *p<0.1; **p<0.05; ***p<0.01

Table 57: Fama-French 5 factor model IT - size sorted 80/20

	SJ	SQ	SQMJ	BJ	BQ	BQMJ	QMJ
MKT	0.686***	0.743***	0.057	0.709***	0.780***	0.071	0.064
	(0.087)	(0.065)	(0.088)	(0.113)	(0.109)	(0.143)	(0.087)
SMB	0.882***	0.664***	−0.219	0.115	−0.109	−0.223	−0.221
	(0.203)	(0.152)	(0.204)	(0.262)	(0.255)	(0.334)	(0.202)
HML	0.506*	−0.043	−0.549**	0.962***	−0.041	−1.000**	−0.776***
	(0.262)	(0.197)	(0.264)	(0.339)	(0.330)	(0.432)	(0.261)
RMW	0.212	0.317	0.105	0.256	0.438	0.182	0.144
	(0.365)	(0.275)	(0.368)	(0.473)	(0.460)	(0.603)	(0.364)
CMA	−0.461	−0.359	0.101	−1.870***	−1.070**	0.806	0.453
	(0.338)	(0.254)	(0.340)	(0.437)	(0.425)	(0.557)	(0.336)
α	0.0003	0.005*	0.005	0.004	0.001	−0.002	0.001
	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
N	188	188	188	188	188	188	188
Adj R^2	0.502	0.584	0.056	0.463	0.363	0.059	0.111

Note: *p<0.1; **p<0.05; ***p<0.01