A thesis presented for the degree of
Master of Financial Economics
Erasmus School of Economics, Erasmus University Rotterdam

Dissecting Anomaly Returns Among High and Low ESG Stocks

Master Thesis

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July 2021

Abstract

Over the last decades, the efficient market hypothesis has frequently been challenged by trading strategies that persistently produced profitable opportunities without extensive fundamental analysis.

These trading patterns are considered anomalous since traditional asset pricing models cannot explain the returns. The rise of ESG investing suggests that investors are not only interested in maximizing financial value anymore. Whether this translates into different behaving stock market anomalies among high and low ESG rated stocks, is an open question. To address this question, I construct double-sorted portfolios to test a variety of trading strategies on high and low ESG stocks. I show that over the last 16 years, sustainable stocks generate significantly different returns relative to non-sustainable stocks if it comes to trading strategies based on operational flexibility, idiosyncratic risk, and quarterly cash flow-to-price. My results shed light on the controversy of efficient markets and suggest that dissecting stocks based on ESG scores could play an important role in explaining potential mispricing aspects in the cross-section of returns.

Keywords: ESG investing, stock market anomalies, market efficiency.

I would like to express my gratitude to my supervisor Ricardo Barahona for his guidance and my friends and family for the continuous support during my years at the ESE.

List of Abbreviations

AT .... Total Assets

BE .... Book Equity

CAPM .... Capital Asset Pricing Model

CMA .... (Conservative-Minus-Aggressive) Investment premium

COGS .... Cost Of Goods Sold

CRSP .... Center For Research in Security Prices

CSR .... Corporate Social Responsibility

DPQ .... Depreciation

dROE .... 4-Quarter Change in Return on Equity

EMH .... Efficient Market Hypothesis

ESG .... Environmental, Social Governance

EW .... Equal Weighted

HmL .... High-Minus-Low (Value Premium)

HML .... High-Minus-Low (portfolio)

IBQ .... Income Before Extraordinary Items

KLD .... Boston Based KLD Research and Analytics, Inc.

LMH .... Low-minus-High (portfolio)

LSEG .... London Stock Exchange Group

MKT .... Market Risk

MVE .... Market Value of Equity

NYSE-EW .... Equal Weighted returns using NYSE Breakpoints

NYSE-VW .... Value Weighted returns using NYSE Breakpoints

OANCFY .... Net Cash flow From Operating Activities

OL .... Operating Leverage

PRC .... Current Share Price

PSTKQ .... Book Value of Preferred Stock

$_{q}$**CFP** .... Quarterly Cash flow-To-Price

$_{q}$**OCFP** .... Quarterly Operating Cash flow-To-Price

R&D .... Research And Development

RET .... Monthly Holding Period Return

RMW .... Robus-Minus-Week (Profitability Spread)

ROE .... Return On Equity

S&P 500 .... Standard & Poor's 500 Index

SEQQ .... Stockholders' Equity

SMB .... Small-Minus-Big (Size Spread)

SRI .... Socially Responsible Investing

TXDITCQ .... Deferred Taxes and Investment Tax Credit

VW .... Value Weighted

XDGA .... General, Administrative and Selling Expenses

Contents

Chapter 1

Introduction

With a fast-growing population, rising levels of emissions, and consumption of natural resources faster than can be replenished, growing environmental and social issues are on the rise (United Nations, 2019). Although these impactful factors have never remained unnoticed, ESG (Environmental, Social, and Governance) integration in portfolio selection has become increasingly popular among investors and asset managers (Lioui, 2018b).

Traditional investment approaches are built on fundamental theories as Modern Portfolio Theory (Markowitz, 1952) and the Efficient Market Hypothesis (EMH) (Fama, 1970). Both theories argue that agents base their investment decisions according to a trade-off only between risk and return. The rise of ESG investing, however, suggests that investors value more than just risk and return. In fact, maximizing financial value on short-term financials seems to be substituted, or at least to some degree, towards long-term value creation by taking into account nonpecuniary investment motivations (Schoenmaker & Schramade, 2019).

The Efficient Market Hypothesis assumes agents to operate rationally and assumes prices to reflect all available information (Fama, 1970). The extent to which this EMH holds is questionable since the existence of stock market anomalies is predominantly used as evidence against this theory (Dumitriu et al., 2012). Besides, there is plenty of evidence from the behavioral finance literature against the idea of perfectly rational agents and efficiently priced markets (Schoenmaker & Schramade, 2019).

Stock market inefficiencies are not only present by the existence of stock market anomalies but seem to play an important role by incorporating environmental risk aspects. Lo (2019) presents an alternative description of markets where the degree of market efficiency is dependent on the evolutionary model of individuals adapting to a changing environment, and where environmental risk factors are not entirely priced in. The reason for this is that not enough investors are examining these new risks (Schoenmaker & Schramade, 2019).

Whether these inefficiencies result in different behaving stock market anomalies that are more prevailed among sustainable investments, is yet to be explored in academic research. There are potentially rational and behavioral explanations why certain trading strategies would perform differently among high and low sustainable stocks. On the one hand, a rational motivation may be that the occurrence of a stock market anomaly differs since low ESG stocks are being more neglected by investors, which makes them less efficiently priced. On the other hand, the difference in occurrence may be explained by a behavioral aspect of decision making that is more pronounced among green stocks (high ESG), causing green stocks to deviate from their efficient prices.

Although there has been plenty of academic research about the existence of stock market anomalies, the causes, and what the behavioral aspects of anomalies are, it is still a grey area for research (Latif et al., 2011). This might have to do with the fact that the potential underlying behavioral reasons cannot be established with full certainty. The occurrence of abnormalities or deviations often seems to disappear, reverse or weaken after anomalies have been documented in academic literature (Schwert, 2003). Therefore, additional research is relevant to develop a better understanding of the debatable behavioral aspects of anomalies and besides, from a social relevance perspective, additional research examines whether profitable trading opportunities still exist for investors in the current markets.

Markets have become more efficient throughout the years. For instance, due to technological transformation, markets have become more liquid and efficiently priced and in addition, technology led to a positive influence on the average trader becoming better informed (Farboodi & Veldkamp, 2020). Moreover, the emergence of quantitative investment strategies has made it easier to exploit trading strategies based on firm characteristics (Farboodi & Veldkamp, 2020).

On the contrary, the proliferation of ESG investing could increase market inefficiency. On the one hand, investors' taste for assets that are willing to forgo financial performance to fulfill their social preferences could negatively impact efficiency (Cao et al., 2019). On the other hand, efficiency is challenged because of sustainability reporting by companies. Some information is argued to be incomplete and lacks credibility and quality, due to highlighting goals and aspirations rather than actual deeds (Paul, 2008).

1.1 Research Objective and Research Question

This research endeavors to contribute to the existing literature regarding stock anomalies with new research in a more recent database. Moreover, it investigates whether trading strategies behave differently among stocks that are classified and perceived to perform better on a wide range of ESG topics. Whether it is based on a rational or a behavioral explanation, there is reason to believe that market efficiency differs among high or low ESG stocks. If these inefficiencies also manifest themselves in the dissimilar occurrence of stock market anomalies, is a central question in this research. For this reason, this research focuses to answer the following research question:

To what extent do stock market anomalies behave differently among high-rated ESG stocks and low-rated ESG stocks in the S&P500 index throughout 2005 until the end of 2020?

The reasons for investigating the constituents included in the Standard & Poor's 500 index (S&P 500) it twofold. Firstly, since this index contains the 500 largest companies listed on the US stock exchange, one may assume that these large-cap stocks are efficiently priced. The existence of return anomalies within this index provides thus impactful evidence against the EMH. Secondly, and more importantly, since ESG is relatively new and lacks a wide availability of data, access to ESG-data is more available for larger-cap stocks than for smaller ones. To come to a comprehensive understanding of how anomaly performance differs between high and low ESG stocks, trading strategies in five different category anomalies will be tested, each with a distinctive number of anomalies per category. Specifically, the category Momentum is characterized by the momentum anomaly (Jegadeesh & Titman, 1993) and intermediate horizon momentum (Novy-Marx, 2012) as a robustness check. In addition, a longer time horizon momentum strategy will be constructed to investigate if the intermediate horizon momentum anomaly is more pronounced in a longer timespan prior to the formation period. Category Value vs Growth is characterized by the quarterly cash flow-to-price anomaly (Lakonishok et al., 1994), supplemented by quarterly operating cash flow-to-price (Desai et al. 2004) as a robustness check. Category profitability includes the 4-quarter change in return on equity (Hou et al., 2020) with return on equity as a robustness check (Hou et al., 2015). Furthermore, category Intangibles is characterized with the operating leverage (Novy-Marx, 2011) and lastly, category Trading Frictions is tested with the low (total) volatility anomaly (Blitz et al., 2007) and idiosyncratic volatility (Ang et al., 2006) as a robustness check.

The findings of this paper reveal that stock markets anomalies still appear to be present in the current US stock market, even among the largest firms. Moreover, this research does not find that merely high or low ESG stocks are more susceptible for anomalies in general but rather exhibit distinctive results among the anomalies. In particular, the momentum strategies and the operating cash flow-to-price anomaly are virtually non-existent among high and low ESG stocks. The cash flow-to-price anomaly is more pronounced among high ESG stocks and is statistically different from low ESG stocks. This conclusion also applies to the operating leverage anomaly. The profitability anomalies appear to be robust among both high and low ESG stocks and are not statistically different. Lastly, although both trading friction anomalies seem to produce significant returns among low ESG stocks, only under idiosyncratic volatility is the long-short portfolio return among high ESG stocks significantly different from that of low ESG stocks.

This paper is organized in the following way. The second chapter details a theoretical overview of the concepts of ESG investing and anomalies, followed by the construction of the hypotheses. After that, the source of the data and the used methodology will be explained. The empirical results will be discussed in Chapter 4, followed by the conclusion and limitations of this paper.

Chapter 2

Literature Review

2.1 ESG

2.1.1 What is ESG Investing

ESG (Environmental, Social, and Governance) investing is a form of sustainable investing. The fundamental difference lies in the fact that sustainable investing practices (synonymously called impact investing) attempts to create a measurable positive effect by investing in assets that could enhance environmental or social aspects in society, where ESG integration under- or overweight assets based on their ESG rating (Zerbib, 2019). This relates impact investing for seeking investments that can help achieve a certain explicit positive outcome (Barber et al., 2021), where ESG investing offers a better balance of providing financial return while still supporting one's ethical values (Cao et al., 2019).

The set of standards that socially conscious investors use to screen potential investments are the Environmental, Social, and Governance criteria. Environmental capture aspects such as carbon emissions, water consumption, and waste generation. The Social criteria examine, among others, how a firm manages relationships with suppliers, employees, and customers. Lastly, governance exhibits how a firm deals with aspects related to their corporate governance, e.g. board diversity, executive pays, and shareholders' rights (Amel-Zadeh & Serafeim, 2017).

ESG aspects have become significantly popular amongst investors and asset management firms. The reasons for this observation can partly be explained by increased awareness of environmental issues, an increase in the availability of information regarding Corporate Social Responsibility (CSR), and the enhanced speed at which information is shared. At the same time, investors put a heavier weight on transparency about corporate social responsibility (Lioui, 2018b).

The idea of investing based on a set of principles, and not merely for profits, is not a new phenomenon. In the 18$^{\text{th}}$ century, Christian groups such as the Methodists and Quakers provided clear guidelines to their disciples over which companies should receive an investment and which are ruled out. The practice of investing based on principles has shown a noticeable effect in society as well. For example, shareholders' influence, together with the recognition of the opportunity to change corporate behavior, has pressured firms to avoid providing capital to South African companies, which is seen as an important factor that helped end the Apartheid (Schroders, 2016).

The large heterogeneity among investors' ethical values affects portfolio choice and consequently equilibrium prices. Since ESG investing is not a standardized approach, a lot of diversity exists among ESG investors. This is similar to the field of ethics, where different answers arise to the same important ethical questions. The extent to which it affects equilibrium prices is dependent on the degree to which investors incorporate ESG in their portfolio choice. For instance, where some investors are unaware of ESG scores and simply seek to maximize their unconditional mean-variance utility, other investors use ESG scores as a primary motivation for investing and exclude assets that do not align with their investment objectives (Pedersen et al., 2020). The exclusionary practices are well known under the concept of sin stocks, where investors exclude stocks of firms in industries as alcohol, tobacco, gambling, and weapons industries (D. Blitz & Fabozzi, 2017). This has been shown to lead to major demand and supply imbalances (Zerbib, 2019).

The proliferation of sustainable investing is observable. This is especially visible by the growing interest of investors in green investments. Sustainable investing has been growing on a large scale in recent years. For example, the total global sustainable investments amounted USD 13.3 trillion in 2012 and since then that number has nearly tripled by 2018. Moreover, ESG integration is now the second-largest sustainable investment strategy under the umbrella of sustainable investing (GSIA, 2013), and is expected to reach a number of assets with an ESG mandate of USD 160 trillion by 2036 (Uzsoki, 2020).

2.1.2 ESG and Traditional Investment Approaches

The rise in ESG investing seems to change the financial focus from a traditional investment approach to a more sustainable one that incorporates environmental, social, and governance aspects (Schoenmaker & Schramade, 2019). Traditional investment approaches are built on neo-classical investment paradigms of the Modern Portfolio Theory by Markowitz (1952) and the Efficient Market Hypothesis by Fama (1970). These theories suggest rational investors that are maximizing return at a given level of risk or minimizing risk at a given level of return. Moreover, these theories also imply that a firm aims to create financial value for shareholders. ESG externalities, however, are not included since these factors are expected to destroy shareholders' wealth (Schoenmaker & Schramade, 2019).

Additionally, the rise in ESG creates controversy regarding classical asset pricing models that generalize investors' objective function using utility over consumption or wealth. The increase in ESG investing suggests that investors also derive utility from positive societal externalities, meaning that investors are willing to pay for impact (Barber et al., 2021).

2.1.3 ESG and (Expected) Stock Performance

Whether investing in future-proof, long-term value-creating companies pay off, differs dramatically across academics and practitioners (Pedersen et al., 2020). For example, Hong & Kacperczyk (2009) argue that ESG integration unquestionably lowers the expected return. Besides, restricting your potential investment universe due to exclusionary practices can lead to deteriorated diversification in one's portfolio and thus increased idiosyncratic risk (Hanicova & Vojtko, 2020). On the other hand, other researchers argue that companies with high ESG scores are expected to report higher excess return, supported by the assumption that market agents carry the irrational belief of ESG factors being a good proxy of a firms' financial soundness (La Torre et al., 2020; Fulton et al., 2012).

When focusing on documented rather than expected financial returns, the results vary as well. Bennani et al. (2018) find that ESG investing was merely profitable since 2014, but no indication of remunerative return was found during the period between 2010 and 2013. Khan et al., (2016) find high ESG scored companies to outperform low ESG companies, where they emphasize that good rating on material sustainability issues drive the outperformance significantly. Friede et al., (2015) state that the majority of research show ambiguous findings on the relation between ESG incorporation and financial return.

Pedersen et al. (2020) state that the outperformance of high ESG stocks depends on whether the value of ESG is not fully priced into the market. According to them, the range of possible equilibria depends on the relative importance of each type of investor, which leads to a relation between expected return and ESG being dependent on how many investors value high ESG stocks and incorporate these aspects into their portfolios. The authors explain that a positive relation between ESG and expected return exists when ESG is not fully priced in but weakens when most investors are willing to accept a lower return for holding more socially responsible stocks.

2.1.4 ESG and Market (In)Efficiencies

There are reasons to believe why ESG negatively affects market efficiency. For instance, investors seem to carry the irrational belief that high ESG scores are a proxy for positive future returns, while no compelling evidence is brought to light to support this notion (Hartzmark & Sussman, 2019). Besides, investors seem to respond heavier to ESG rating downgrades than to the same degree in upgrades (Nagy et al., 2013). Price fluctuations due to changes in ESG ratings, rather than new information about fundamentals, show that investors' feeling about an investment is influencing the buy or sell decision rather than trading on attributes related to performance.

Furthermore, an additional issue that affects market efficiency among ESG stocks, has to do with the objectivity of the measured ESG score (Hanicova & Vojtko, 2020). Each data provider uses different criteria to evaluate individual companies. Nevertheless, the average correlation between scores among five well-known ESG score providers differs from 42% to 74% (Berg et al., 2019). This makes it incredibly challenging for investors to price ESG scores in the market correctly (Hanicova & Vojtko, 2020).

Since the existence of stock market anomalies is repetitively used to question the efficiency of stock markets (Dumitriu et al., 2012), the examples that affect the ability to price ESG (risk) in the market accurately make it relevant to investigate whether stocks market anomalies also behave differently between high and low ESG rated stocks. But before formulating the expected relationship between these facets, it is first discussed what defines an anomaly.

2.2 Stock Market Anomalies

2.2.1 Identifying an Anomaly

When one states that a stock market anomaly has been captured, it builds upon the concept of efficient markets and how it relates to trading strategies. Fama (1970) describes market efficiency as the relation between information and stock prices. As a result of this theory, The EMH is presented as a cornerstone in financing and investment theory. It states that prices reflect all relevant information, which means that an investor would not be able to structurally obtain better returns than the average market, except through luck. In case irrational investors would cause unexpected price movement, arbitrageurs would arbitrate away these movements so that prices converge to their true fundamental values. An anomaly, however, is a situation where prices are not fully reflecting all relevant information, and thus creating an exploitable trading opportunity through investment strategies (Meier, 2014). An anomaly is defined as periodically recurring stock price patterns that have no empirically verified or theoretical conclusive explanation (van der Sar, 2018).

2.2.2 Persistence of Anomalies

Some argue that investors behave more in line with an adaptive-efficient market (Daniel & Titman, 1999; Lo, 2005). They believe that markets become efficient once anomalies have been detected and documented. Once agents are aware of those anomalies and trade on them, they should disappear and prices return to their efficient values. Moreover, French (1980) adds to this idea that the temporary existence of abnormalities is not an actual violation of the EMH, since agents are unaware of arbitrage opportunities before they are documented in academic research. Remarkably, the momentum anomaly did not disappear after it has been documented (Moskowitz et al., 2012). This persistent appearance suggests that one may even question whether the adaptive efficient market theory holds.

2.3 Connecting ESG & Anomalies

2.3.1 ESG Score in Relation to Anomalies

Whether anomaly performance may be different for high versus low ESG stocks based on a behavioral or a rational reason, is debatable. This has to do with the fact that academics are still not fully capable of stating the behavioral aspects of recurring abnormalities, especially since deviations are not consistent in their occurrence (Latif et al., 2011).

A rational explanation why low ESG stocks may experience more inefficiencies than high ESG stocks may be explained by the fact that these stocks are being more neglected. Zerbib (2019) describes how sustainable investing affects asset returns through exclusionary screening and ESG integration. His perspective is in line with the thoughts of Merton (1987)[1] that neglected stocks can depress stock prices. High sustainable companies experience a higher demand than non-sustainable companies, which results in these higher demanded stocks become considerably less risky due to their decreased cost of capital. The opposite holds for non-sustainable stocks, which become significantly riskier due to the exclusionary screening (Zerbib, 2019).

On the contrary, A behavioral explanation of why low ESG stocks may experience divergence in (price) efficiency compared to high ESG stocks, may have to do with investors' nonfinancial motives and sentiment towards ESG for buying high ESG stocks, which could drive stock prices away from their fundamentals. Another potential explanation might be that the underlying behavior reason that causes an anomaly to persist, would be amplified in particular among high or low ESG stocks. Whether the results conform better to an interpretation with respect to a behavioral motivation, will follow in *Chapter 4*. First, the separate anomalies and their potential reason for their occurrence will be discussed.

2.3.2 Momentum Anomaly

The momentum anomaly has been documented by Jegadeesh & Titman (1993) and states that investment strategies that buy winning stocks according to their recent past performance, and sell losing stocks according to their recent past performance, generate significant positive returns. Their most lucrative strategy selects stocks based on their previous 12 months and has a holding period of 3 months. This strategy yields around 15% annually. Their zero-cost investment strategies show significant abnormal returns over the period between 1965 to 1989. By testing their strategies, they acknowledge that

[1] Although Merton (1987) highlights the notion of incomplete information that causes stock prices to become depressed, rather than deliberate exclusionary practices, the idea of certain assets producing anomalous behavior or becoming underpriced is also applicable in the context of ESG investing.

once there is a lag between the holding and the formation period, returns are slightly higher as a lag accounts for short-term reversal. What makes this anomaly a puzzling phenomenon is the fact that trading on past performance relates to asset characteristics, rather than firm characteristics and thus questions the EMH.

For this reason, Jegadeesh and Titman (1993) state that the momentum phenomenon is more consistent with delayed price reactions to firm-specific information and thus conform better to a behavioral explanation, rather than (systematic) risk explanations. The authors explain that individuals may over- or underreact to information that leads to positive feedback trading, which is seen to be an explanation for the appearance of this anomaly.

In a later study regarding the momentum strategy, Novy-Marx (2012) refutes the common belief that momentum is driven by the tendency of an object in motion to stay in motion, but finds that the average return predictability is higher when observing a stock's intermediate horizon past performance, which is measured over the period t-12 to t-7 before holding period. The intermediate horizon past performance significantly outperforms the average return of stocks compared to the original momentum strategy documented by Jegadeesh and Titman and implies a diminishing predictive power of recent returns. Notably, the intermediate momentum strategy seems to perform the best among the largest, most liquid stocks.

Price Momentum and ESG

Whether the behavioral aspects that incentivize investors to over- or underreact to information, can cause more positive feedback trading among (non)green investments, may be supported by the idea that sentiment towards sustainability can amplify this behavior. Lioui (2018b) investigates the impact of a sentiment index on the market price of risk of ESG and concludes that aggregate ESG is strongly impacted by sentiment. In another publication, Lioui (2018a) emphasizes that advocates of ESG investments and asset managers that integrate ESG claim that in the long run, such a strategy will be paying off, implicitly meaning that in the short term it would not result in outperformance. This can be explained by the fact that investments in green technology are expensive and include high fixed costs, which are necessary for the transition to a more sustainable economic model to compete and thrive as a business longer-term (Dyllick and Muff 2016; Tirole 2017).

The fact that green technology is expensive and is expected to pay off only in the long term, suggests that investors with a short-term time horizon may be less interested to invest in these high ESG ranked stocks. This may improve stability in green stocks since most long-term investors hold these securities. As instability in stock prices is associated with speculators being attracted to the market (Chakrabarti & Sen, 2020), the idea of more patient capital for outperformance long term, suggests that (profitable) momentum strategies are less likely to appear among high ESG companies compared to low ESG companies. For this reason, the first hypothesis is as follows:

H1: Investing based on the momentum strategy in high ESG score companies will result in less outperformance than investing based on the momentum strategy in low ESG score companies.

2.3.3 Quarterly Cash Flow-to-Price Anomaly

Value strategies entail buying stocks with low prices relative to measures of fundamental value, e.g., earnings, book value, and cash flow. For example, Chan et al. (1991)

show that a high ratio of cash flow-to-price predicts a higher return. While this is only one example of a value strategy they document, interestingly many have outperformed the market. Bondt & Thaler (1987) find evidence that extreme 'loser' portfolios outperform the market between 1926 and 1982, Rosenberg et al. (1985) show that high book-to-market valuation tends to outperform the market, and Fama & French (1992) find that stocks with high earnings-relative-to-price generate high risk-adjusted returns.

Although these anomalous returns cannot be explained without some controversy, Lakonishok et al. (1994) explain the potential behavioral reasons why value strategies tend to outperform, and why they are *contrarian* to *naïve strategies*, which are mostly followed by the majority of investors. For instance, investors that follow naïve strategies, may overreact to good or bad news, extrapolate past earning growth too far ahead or carry the irrational belief of perceiving a well-run company as being a good investment, regardless of the price one pays. These reasons contribute to investors overpaying for *glamour stocks*, while overreacting to stocks that did not perform well in the past, resulting in underpriced *value stocks* (Lakonishok et al., 1994). On the contrary, Fama & French (1992) proposed a rational justification why value stocks tend to outperform, namely, that these stocks are fundamentally riskier. Nevertheless, Lakonishok et al. (1994) find little to no evidence for the view that the observed assets are fundamentally riskier.

One of the value strategies that Lakonishok et al. (1994) propose, consist of sorting stocks based on the ratio of cash flow-to-price, where high cash flow-to-price are identified with value stocks since the proxy for future growth rate is low. Although they perform 4 different value strategies (based on cash flow, book-to-market, past growth-in-sales, and earnings), the largest long-short portfolio return is achieved by contrarian investors using cash flow-to-price as a measure of fundamental value, namely 11 percent annually (Lakonishok et al., 1994).

In the paper of Hou et al. (2020), they find that the significance level enhances considerably if they look at quarterly cash flow-to-price instead. This observation holds for value-weighted[2] and equally-weighted returns. For this reason, the quarterly cash flow-to-price anomaly is used in this research as a primary value strategy to investigate how the value vs growth anomaly category differs in performance between low and high ESG stocks. On top of this, the quarterly operating cash flow-to-price, inspired by the original paper of Desai et al. (2004) and the paper of Hou et al. (2020), will be constructed as a robustness test for the cash flow-to-price anomaly. Desai et al. (2004) state that the operating cash flow-to-price ($_{\text{q}}$OCFP) anomaly is subject to two plausible interpretations based on the reader's priors. On the one hand, their documented anomaly could be seen as a separate variable that captures both value-glamour and accruals mispricing attributes. On the other hand, it could be that one interprets their findings as an expanded value-glamour proxy, if one views the documented anomaly broadly as one of the fundamentals-to-price anomalies.

Quarterly Cash Flow-to-Price and ESG

Although there is some agreement that value strategies have outperformed naïve strategies, the interpretation of why remains controversial. If value stocks tend to outperform because investors tend to extrapolate past earning growth too far ahead, as Lakonishok et al. (1994) explain, one might think that financially sound firms (glamour stocks) are also the highest ESG ranked companies since these stocks have the resources to invest in ESG practices. This would then suggest that value strategies would be more profitable for low ESG score stocks. Nevertheless, this causation is unclear, since it is not clear whether

[2]The observation of value weighted returns showing highly significant returns in a universe consisting of all stocks is especially interesting for this research as I observe the largest US companies, while equally weighted capture a larger degree of small firms.

high ESG ranked firms receive more recourses, or that profitable firms are simply more capable of investing in areas that positively influence their ESG score (Campagna et al., 2020).

On the other hand, the superior return of value stocks could also be explained by the fact that most (naïve) investors prefer to invest in more 'prudent' investments as glamour stocks, simply because they have shorter time horizons than would be required for value strategies to systematically pay off (Lakonishok et al., 1994). In this case, one could assume that value-investors with longer time horizons are more associated with high ESG rated stocks. This can be explained by the fact that both value and ESG investors carry the same mentality of focusing on long-term value creation. Whether the first or latter motivation is more likely, is controversial. For this reason, the second hypothesis states the null hypothesis of no differences in return and thus is as follows:

H2: Investing based on the quarterly cash flow-to-price-anomaly in high ESG score companies, will result in no different return than following the value strategy in low ESG score companies.

4-Quarter Change in Return on Equity Anomaly

Return on equity (ROE) is used as a profitability measure and shows how well a firm generates profit for its shareholders. It displays the efficiency at which a company generates profits from shareholder investments. A declining ROE indicates that the company is becoming less efficient at creating profits for its shareholders. Notably, an increasing ROE is a sound indication of increasing efficiency, although it does not by definition mean more profit for common shareholders if the preferred shareholders take away the increased value creation (Hendricks, 2020).

Many different profitability measures have been proposed to predict returns. George et al., (2018) show that investing in stocks with a high ratio of current price-to-52-week-high, earn high future returns. Ball et al. (2016) create a measure of cash-based operating profitability, which seems to predict positive returns. Hou et al. contribute to the number of profitability measures by using Return on equity (ROE) in their paper of 2015 and the 4-quarter change in return on equity (dROE) in their paper of 2020 as predicting measures in a dataset starting from 1967 and ending in 2018. While both are found significant at 5%, dROE has been found significant at 1% value- and equally weighted. According to Hou et al. (2020), investing is based on the 4-quarter change in return on equity, resulting in a monthly average return of high-minus-low decile portfolio return between 0.88% (value-weighted) and 1.56% (equally weighted). This was higher than the return based on ROE, which resulted in a value-weighted and equally weighted monthly return of 0.77% and 1.36% respectively.

In a later publication, they explain why they use, among others, the 4-quarter change in return on equity as a growth predictor (Hou et al., 2021). Based on the investment theory, companies with high expected investment growth should outperform companies with low expected investment growth, holding expected profitability and current investment constant. This intuition behind this theory is that if one expects investment next period to be high, the present value of cash flows from the next periods onwards should be high as well. If one tilts towards a present value calculation, the benefit of investing in the current period should equally be high.

4-Quarter Change in Return on Equity and ESG

High ESG rated firms seem to be related to higher levels of profitability (Campagna et al., 2020). This might be explained by the fact that these firms generate sales using their assets more efficiently, which could consequently result in a higher ROE. Specifically, if a firm scores high on the social criteria, which examines how a firm manages its relation for example with employees, it tends to boost productivity, since employee motivation is gradually but firmly established by a sense of purpose (Henisz et al., 2019). This results in higher revenue, and with an efficient allocation of capital, this could result in higher profit as well. Furthermore, since high ESG firms tend to reduce legal and regulatory interventions, and besides save a considerable amount of costs if they invest in environmentally friendly policies that can be used as a competitive advantage, they seem to reduce pollution prevention pays (Henisz et al., 2019). Lastly, board gender diversity is captured by the governance criteria, which seems to be positively correlated with profitability (Dang et al., 2020).

Although various arguments point towards a one-sided view of direction why high firms with a high ESG rating, in theory, are expected to earn a higher return on equity, this might not always be the case. For instance, a high ESG score could also be assigned to firms with bad corporate governance and less value creation for shareholders. Gompers et al. (2003) find, by disentangling the Governance factor performance, that strong governance performance is associated with higher risk-adjusted returns for investors. Nevertheless, what the governance score doesn't capture, is that if a CEO allocates lots of resources towards sustainable issues, instead of investing in profitable investment opportunities that shareholders appointed the CEO for, the high allocated ESG score on this aspect does not create a higher return on equity, at least for the short term. Besides, although the use of one numerical ESG score provides a useful overview of a firm's ESG performance, the disadvantage is that the different factors have a different impact on performance. While some initiatives may add value, the other ones may be value-destroying (Galema et al., 2008). For this reason, it is unclear whether a high ESG score will unambiguously result in a higher return on equity for stockholders and thus there is not enough compelling evidence found in literature why one can expect that trading on dROE will result in more profit among high nor low ESG stocks. For this reason, the third hypothesis will be stated as the null hypothesis, and is as follows:

H3: Investing based on the 4-quarter change in return on equity in high ESG score companies, will result in no different return than investing in low ESG scored companies using the same metric.

2.3.4 Operating Leverage Anomaly

Operating leverage is a cost accounting formula that addresses the proportion of fixed costs relative to variable/total costs and is, therefore, an important measure of a firm's cost structure. A higher ratio means that a firm is subject to higher fixed claims, which consequently makes firms' profitability more susceptive for volatility since they are less flexible to adapt their total costs to new levels of demand (Novy-Marx, 2011). Lev (1974), and later Mandelker & Rhee (1984), studied the relationship between systematic risk and operating leverage and found a positive link. Novy-Marx (2011) contributed to these findings by showing that firms with leveraged assets (in terms of operating leverage and not financial leverage) significantly outperform firms with unlevered assets. Namely, over a sample period starting from 1963 and ending in 2018, the levered portfolio earned value-weighted 44 basis points (per month) more than the unlevered portfolio, where equally weighted resulted in 51 more basis points.

Since cost structures can vary considerably among competitors in the same industry, the degree to which a company can increase operating income by simply increasing revenue differs. This consequently makes the effect of changes in sales not homogeneous for every rival and thus affects the profitability and operating risk of a company in a different magnitude (Z. Chen et al., 2019). Since a higher fixed cost claim restricts a firm's flexibility to adjust to a change in demand, it makes levered firms riskier and thus positively affecting expected return. This may explain why Novy-Marx (2011) finds significant evidence in favor of the operating leverage hypothesis, which predicts that firms with a higher portion of annual operating costs should outperform firms with lower annual operating costs.

Operating Leverage and ESG

The potential relation between ESG and intangibles may be captured by the fact that high ESG companies tend to invest considerably in Research and Development (R&D) (Campagna et al., 2020). This makes sense since these companies invest heavily in the future. Moreover, R&D expense may also be a form of fixed costs, since intangible assets are more subject to larger adjustment costs than tangible assets (Liu & Shen, 2012).

Furthermore, according to Perez-Batres et al. (2012), high levels of ESG performance necessitate costly maintenance of relationships with equity holders and thus increases a companies' fixed costs. This may be explained by ESG investments being associated with high agency costs, since managers can improve their own reputation by investing in ESG, at the expense of investors. Once investors adopt ESG by putting heavier weights on more sustainable aspects, they may put greater relevance to the larger fixed costs which are associated with enhanced ESG practices (Tommaso & Thornton, 2020). This might suggest that investors perceive larger fixed claims, among high ESG rated stocks, less risky compared to high fixed costs associated with low ESG rated firms. According to the operating leverage hypothesis, the higher fixed claims would restrict a firm to adapt to new levels of demand, which makes these levered firms thus riskier. But since high ESG rated firms are associated with higher fixed costs as they invest more in a greener and future-proof business model, it is not clear whether investors value differences in operating leverage differently for high and low ESG rated companies. This makes it ambiguous whether the predictive power of the operating leverage hypothesis is similar under both high and low ESG rated firms. For this reason, the fourth hypothesis states the null hypothesis of no difference and is as follows:

H4: Investing based on the operating leverage will result in no difference in return for high ESG scored companies compared to low ESG scored companies.

2.3.5 Low Volatility Anomaly

The volatility effect refers to the empirical findings by Blitz & Vliet (2007) that stocks with low historical volatility perform considerably better than stocks with high historical volatility in the same period. They find evidence for the presence of the volatility effect in the many international markets over a period between 1986 and 2006. Their annual alpha spreads of comparing their top and bottom decile portfolio are around 12 percentage and contribute to the idea that low-risk stocks are outstandingly attractive. This is in line with the findings of Ang et al. (2006), which show that over a period between 1963 and 2000, U.S. stocks with high idiosyncratic volatility have remarkably low average returns. Both these findings challenge the efficient market theory by creating a portfolio that generates comparable returns as that market portfolio, but with lower risk levels.

Blitz and Vliet (2007) present several explanations for the documented volatility effect. Firstly, using leverage to optimally benefit from the low-risk stock returns, might conflict with investors' willingness to risk-taking. In addition, borrowing restrictions is also be seen as one of the reasons why low-volatility stocks perform consistently well (Black, 1972). Another potential explanation for the observed volatility effect is that investing by asset managers is benchmark-driven, which incentivizes these managers to allocate capital into high volatility or high beta stocks, to outperform the benchmark. This consequently increases the prices of riskier stocks, while underpricing low-risk stocks.

Lastly, behavioral biases among private investors may also explain the volatility effect (Blitz & Vliet, 2007). Consistent with Shefrin & Statman's (2000) explanation of having two layers of aspiration, where one layer is designed for a shot at riches, explains why private equity investors are willing to overpay for high-risk stocks and leaving low-risk stocks to be underpriced. Ang et al. (2006) state in their paper that the robust co-movement in low average return to high idiosyncratic volatility across several countries, implies that factors not easily diversifiable create a basis for the observed phenomenon rather than justifications based on trading frictions, higher moments, or risk loadings. Their strong economically and statistically relevant returns point towards a global puzzling phenomenon.

Low Volatility and ESG

According to Kumar et al. (2016), academics generally agree that high ESG stocks bear lower risk. His explanation for this is that firms that incorporate ESG practices, experience decreased regulatory and reputational risk and decreased instability in profitability. Godfrey (2005) explains that CSR behavior by firms may be implemented to reduce exposure to risk, making SRI more an aspect of risk management than putting ethical values first.

Padysak (2020) investigates the risk-adjusted returns of ESG and finds that the returns of high ESG stocks tend to be less volatile compared to low ESG stocks. Also, Campagna et al. (2020) find a negative correlation between ESG performance and volatility. They argue that high-ESG firms tend to be larger[3] and the lower volatility in return may be explained by the fact that larger companies tend to be more diversified. Furthermore, Lioui (2018b) tests whether ESG risk is priced and finds that high-volatility and high-beta firms, which are usually smaller, tend to underperform compared to low-volatility firms. Nevertheless, even though larger firms may perform better positive CSR, their ESG exposure is considerably larger. He explains this by stating that because of their sizes they are most harmful to the environment as well, which is priced by the market. For this reason, he states that ESG exposure could potentially explain the low volatility anomaly.

Previous literature has highlighted that high ESG rated stocks are associated with less volatility. However, whether investors trading on volatility also earn more return by investing in high ESG rated firms, or whether investors care more about the differences in risk between these stocks, remains unanswered. It might be that since high ESG firms are generally associated with less volatility, trading according to the low volatility strategy will result in a lower return for high ESG stocks since the relative difference between the top and bottom decile is much narrower among high ESG stocks compared to low ESG stocks. However, no clear distinction based on theory can be established.

[3]It should be noted that entire ESG rated universe generally consists of larger firms since they attract more attention and dedicate more resources to reporting (Boffo & Patalano, 2020). This makes it rather a relative comparison.

For this reason, it is unclear whether trading on the low-volatility anomaly generates more or less return among high ESG firms. Therefore, the fifth and last hypothesis states the null hypothesis and is as follows:

H5: Investing based on the low volatility anomaly will result in no difference in return among high ESG score companies compared to low ESG score companies.

Chapter 3

Data and Methodology

3.1 Data Selection

3.1.1 ESG Rating Data

Since ESG investing is becoming mainstream, and the pandemic has accelerated its portfolio integration (Abhayawansa & Tyagi, 2021), the demand for data has been intensified. This creates the opportunity for agencies offering these products for investors, regulators but also academics.

As shown by Berg et al. (2019), the divergence of ESG ratings among different rating agencies differs considerably. With an average of 61% correlation between the different scores of 5 major agencies (Sustainalytics, Asset4, KLD, Vigeo-Eiris, and RebocoSAM), one can argue that the reliability of ESG data is questionable, let alone the ability to price ESG scores in the market correctly. This makes it also challenging for academics to conclude whether their findings regarding ESG stocks are reliable and valid.

The reason for this significant divergence in data to exist is due to differences in defining ESG constructs and divergence in methodology for measuring ESG performance of companies. Every agency constructs its ESG rating in a different approach, by weighting, defining, and composing their concerned factor in a unique way (Abhayawansa & Tyagi, 2021). Besides, Dorfleitner et al. (2015) explain that methodological differences arise since every rating agency differs in the level of detail for developing their rating. These remarks do not mean that the use of ESG data cannot be used. It does illustrate, however, that one should know the differences between the ratings to come to a comprehensive decision on which rating to use for educational purposes. Among the leading ESG data providers, MSCI (formerly known as KLD) and Refinitiv (formerly known as Asset4) are both seen as the largest providers with a global scope and more importantly, both are available for research purposes at the Erasmus University. For this reason, the two data providers and its methodological differences will first be clarified, before explaining which is preferred for this research.

3.1.2 MSCI

The MSCI ESG stats database is constructed by Boston Based KLD Research and Analytics, Inc. (KLD) and is emerged out of four rating agencies, namely: Innovest, GMI Rating, IRRC, and KLD. With a database that starts from 1990 and consists of 37 ESG key points, they try to focus on the intersection between a firm's core business and industry issues, by creating a relative measure to display a firm's ESG related performance on an AAA-CCC scale (MSCI, 2015). The way they construct a relative measure is by defining the number of categories for a certain aspect. Within a category, many criteria describe a defined ESG performance in either 'good' or 'poor.' After setting these criteria, MSCI uses all relevant and public information (e.g. external sources or publicly reported information by firms) regarding ESG data to determine a companies' exposure to industry-specific risks, based on its business activities regarding the concerned element (Lins et al., 2017). After assigning percentage weights to each ESG risk, in line with a firm's time horizon and impact, they combine and normalize the ESG scores relative to industry peers, which results in an overall ESG rating (MSCI, 2015).

Its relative performance scale explains how a certain company's ESG performance relates to that of its industry peers. The Key Issue Scores provide valuable and detailed information about a subset of companies operating in the same industry. Besides, it helps to distinguish competitors from each other. However, this clear relative distinction makes it hard to compare between companies of different industries, since it lacks an absolute measure.

3.1.3 Refinitiv

Refinitiv, as part of the London Stock Exchange Group (LSEG), currently manages the Thomson Reuters ESG score database, and access is provided through Eikon. The database consists mainly of data from ASSET4 and discloses sustainability information that starts from 2002. It consists of 450 key metrics and tries to assess the risks and opportunities faced by firms that deal with ESG exposure, by creating an absolute numerical score that is scaled to range between 0 (worst) and 100 (best) (Refinitiv, 2021a). The way they construct this score is by first dividing the three main pillars 'E', 'S', and 'G', into several categories. Each category is reflecting a firm's performance in that specific field of corporate social responsibility. By using a percentile rank scoring methodology, over 450 firm-specific ESG measures are converted into 178 indicators. Each indicator is then weighted according to their concerning industry and then translated into one absolute numeric score, which can easily be used across companies in different industries (Bofinger et al., 2020).

3.1.4 Choice of Data Provider

Despite the fact that MSCI is widely used in academic literature, probably because of its extended range starting from 1990, the use of Refinitiv's ESG score seems to conform better to this research. This is due to two main reasons. First, since Refinitiv uses an absolute measure, rather than a relative measure that MSCI uses, it makes it easier to compare ESG performance between several companies from different industries. Besides, the relative performance measure makes it hard to construct portfolios of stocks from several industries by purely basing them on their ESG score. Second, MSCI, and specifically KLD, has been criticized due to a lack of objectivity, and more importantly, their assessment of constructing a score is also focused on historical CSR performance. Refinitiv however, is considered to use a forward-looking approach (Hawley, 2017). Since this research is based on investors having a forward-looking investment approach, combined with the preferred use of absolute measures, Refinitiv's ESG scores are favored over the use of MSCI ESG scores.

3.2 The Impact of Data Availability on Portfolio Construction

The Refinitiv's database discloses sustainability information from 2002 onwards. Not only does the number of rated companies grow on an annual basis, but the growing interest of investors in sustainability throughout the years is accompanied by a rising average score per year. This can be inferred from *Table 3.1 (Panel A)*. Since the start of disclosing ESG scores, a consistent and continuously rising trend in improvements can be observed, accompanied by a decreasing divergence among firms. This suggests that progressively more companies show improvements in their commitment towards ESG integration.

Apart from the noticeable visualization of expanding ESG integration by firms, the number of firms rated within the S&P 500 is also increasing. This can be seen in *Table 3.1 (Panel B)*, where the total amount of companies that Refinitiv reported an ESG score of is displayed throughout the years. From the 500 firms considered, less than half of the firms were rated in the years 2002 and 2003. This affects the choice of portfolio construction within this research since a methodology will be used of double-sorting stocks into portfolios, based on ESG score and the corresponding anomaly value.

In case all the S&P 500 constituents are rated, splitting the 500 firms into 3 parts based on ESG scores (high-, moderate-, and low-ESG)[1], while using decile portfolios for a single-sort on anomaly values, would result in around 16-17 stocks per double-sorted portfolio. Alas, the database lacks data, especially in the earlier years of reporting. Specifically, Refinitiv's ESG rated database reflects only a maximum of 224 firms in the years 2002 and 2003, which makes the use of a 103 double-sort detrimental. Namely, this would result in an average of ≈ 7.5 stocks within each portfolio, which increases the possibility that each portfolio suffers from a lack of diversification, since not enough stocks are included to diversify most of the idiosyncratic risk.

A method to increase the number of stocks within a double-sorted portfolio, while preserving the use of terciles for sorts based on ESG score, is reducing the number of quantiles for the considered anomalies. However, the consequence of using a lower cut point for dividing stocks into portfolios, is that the high-minus-low portfolio captures a less clear anomaly effect. For this reason, the decision is based on how many stocks should at least be included within each portfolio to diversify most of the idiosyncratic risk. Notably, most academics and practitioners have dissenting opinions on how many stocks that should be. Reilly & Brown (2011) state that the use of 12 to 18 stocks per portfolio will provide sufficient diversification. They state that around 90% of the maximum benefit of diversification was obtained from portfolios of 12 to 18 stocks. Newbould & Poon (1993) claim that a minimum of 8 to 20 stocks is sufficient to reap diversification benefits, which is similar to the conclusion of Clark (1991). In addition, Newbould & Poon state that the actual amount of stocks also depend on the universe of stocks being analyzed. This by itself is relatable to ESG investors since exclusionary practices implicitly mean that investors are willing to give up some diversification benefits.

Despite the controversy and other practitioners who claim that more stocks are required to benefit from sufficient diversification (e.g. Fisher & Lorie (1970); Statman, (1987); Domian et al. (2003)) this paper requires a minimum of 12 stocks for each (double-sorted) portfolio.

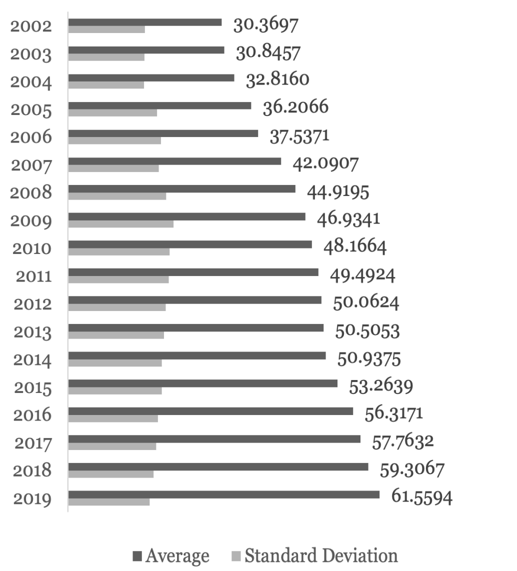
As a result, the use of deciles in a double-sorted (103) procedure is not sufficient to meet this criterion. For this reason, the use of octiles for anomaly sorts, accompanied by the use of terciles for the ESG scores have been chosen. Since Refinitiv suffers from a shortage of data in the years 2002 and 2003, this paper eliminates these years and conducts the analysis of double-sorts (83) from 2004 until 2019 (fiscal years). This elimination of two years results in a minimum number of stocks per portfolio of 12 in 2004 and a maximum number of stocks per portfolio of 21 in 2018.

[1]The process of splitting the ESG sorted stocks in three groups have been preferred over splitting the data based on the median value to ensure a purer effect and focus more on the extremer ESG values.

Table 3.1: *Panel A displays the average and standard deviation of the ESG scores that are included in the database of Refinitiv concerning the SP500 index. Panel B displays the number of companies rated by Refinitiv within the SP 500 index throughout the years. The 500 companies included in the index reflect the composition as of April 2021.*

Panel A

Average and standard deviation of ESG score per year



Panel B

Year	Number of firms rated by Refinitiv
2002	223
2003	224
2004	289
2005	336
2006	341
2007	360
2008	395
2009	417
2010	33
2011	440
2012	441
2013	448
2014	459
2015	488
2016	491
2017	494
2018	494
2019	477

3.3 Financial Data Sources

After having discussed the source of the ESG ratings and the influence it has on the choice of breakpoints for a double-sort methodology, the several databases used to obtain all necessary information will be discussed. Starting with the composition of constituents of the S&P500 index.

In April 2021, the constituents of the SP500 are obtained from Reuters to reflect a recent composition of firms that are included in the index. Index components that were replaced by other components throughout the years of the data sample are not considered, since these companies predominantly lag ESG data. The initial sample is extended by merging monthly stock data of the US-listed companies from the CRSP database, which encompasses 16 calendar years, starting on the 1st of January 2005 and ending on the 31st of December 2020. The dataset contains only US equities listed on the AMEX, NASDAQ, and the NYSE. Hereafter, annual and quarterly accounting data has been collected from the CRSP-Compustat merged database. In addition to this, the Kenneth French's Data library is used to retrieve the 3- and 5- factor models, which include the risk factors related to market risk (MKT), size (SMB), value (HmL), profitability (RMW), and investment (CMA).

3.4 Anomalies Defined

Before explaining which transformations and choices have been made regarding the final merged data sample, first will be explained which variables have been collected for the investigated trading strategies and how the anomalies are defined based on single-sorted portfolios.

When it comes to the category momentum anomalies, three momentum strategies have been tested. Firstly, the momentum strategy is analogous to that of Jegadeesh's and Titman's paper (1993), which is based on the accumulated returns of t-12 until t-2 before the holding period. Like their approach, a one-month lag between formation and holding period has been implemented to account for short-term reversal. Secondly, the intermediate horizon anomaly of Novy-Marx (2012), that takes the accumulated return of t-12 through t-7 into account before the holding period. Again, excluding one month between portfolio formation. Lastly, a new momentum strategy has been constructed to investigate a longer horizon prior to the holding period than that of Novy Marx. Specifically, in contrast to Novy-Marx's intermediate horizon that takes the first 6 months of the preceding year into account, the longer horizon momentum strategy takes the accumulated return of t-18 through t-7 into consideration, once again, excluding one month between formation and holding period. This effectively prologues the formation period of Novy-Marx's momentum strategy to an entire year and seeks to capture a longer delayed price reaction of investors. For each distinct momentum strategy, stocks are allocated into portfolios (octiles) at the start of each month t based on the corresponding accumulated return in the formation period. All the momentum strategies are constructed based on monthly holding period return (item RET; CRSP) and consist of a one-month holding period. The portfolios are rebalanced every month.

For examining the Category Value vs Growth anomalies, the quarterly cash flow-to-price ($_{\text{q}}$CFP) anomaly and the quarterly operating cash flow-to-price ($_{\text{q}}$OCFP) anomaly have been investigated. At the start of each month t, stocks have been split into octiles based on their quarterly (operating) cash flow-to-price. Following Hou et al. (2020), the quarterly (operating) cash flow-to-price for a firm at month t corresponds to the latest fiscal quarter finishing at least 4 months prior to the holding period, divided by the lagged market value of equity (MVE). MVE has been calculated by multiplying the total shares outstanding (item SHROUT; CRSP) and a firm's current share price (item PRC; CRSP). Quarterly cash flows are retrieved from Compustat's quarterly database and are the sum of depreciation (Compustat item DPQ) and income before extraordinary items (Compustat item IBQ). Operating cash flow is defined as net cash flow from operating activities (item OANCFY; Compustat) following. Firms with a negative cash flow are excluded. For the robustness test ($_{\text{q}}$CFP), firms are excluded in the case of a negative operating cash flow-to-price. Monthly octile returns are calculated for the current month t and are monthly rebalanced at the start of the month (t+1).

For the Category Intangibles, which contains the operating leverage (OL) anomaly, the methodology of Novy-Marx (2011) has been followed, which defines OL as the sum of (annual items) cost of goods sold (item COGS; Compustat) and general, administrative, and selling expenses (item XDGA; Compustat), scaled by total assets (item AT; Compustat). Portfolios are formed in June of each year, using the accounting data from the fiscal year ending one year prior (t-1) to the formation period. Octile portfolio returns are computed monthly from July of year t to June t+1.

The category trading frictions are characterized in this paper as the low (total) volatility anomaly by Blitz et al. (2007) and the low volatility anomaly based on idiosyncratic risk by Ang et al. (2006). Both these anomalies are constructed using monthly holding period return (item RET; CRSP). Total volatility as documented by Blitz et al. (2007) has been estimated as a stock's monthly return standard deviation using a rolling window on the last 36 monthly observations (3 years). For the purpose of this research, it is required for a firm to have a minimum of 30 observations to be included in the analysis. Idiosyncratic volatility as documented by Ang et al. (2006) has been used as a robustness test and uses a similar rolling window style as total volatility, requiring the formation period to have at least 30 observations to estimate the standard deviation on residual return. Following the methodology of the original paper, idiosyncratic volatility has been specified by the standard deviation of the residuals $\epsilon_{i,t}$ after regressing monthly returns $R_{i,t}$ of a firm's stock in month t with respect to the Fama-French three factors, which is as follows:

$$R_{i,t} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HmL_t + \epsilon_{i,t}$$

Where MKT, SMB, and HmL represent the market, size, and value factor respectively. For both volatility trading strategies, at the start of month t, stocks are split into octiles based on the estimated volatility from month t-1. Monthly octile returns are calculated and portfolios are rebalanced on a monthly basis. The last Category anomaly tests profitability by constructing a trading strategy using the 4-quarter change in return on equity (dROE), which entails the difference between the return on equity at t=1 minus t-4 (in quarters). Return on equity (ROE) is calculated by using income before extraordinary items (item IBQ; Compustat) divided by a quarter lagged book equity, analogous to Hou et al. (2015). Book equity is calculated by the sum of shareholder's equity, deferred taxes, and investment tax credit (item TXDITCQ; Compustat) minus the book value of preferred stock (item PSTKQ; Compustat). Stockholders' equity (item SEQQ; Compustat) has been used as shareholders' equity. At the start of each month t, stocks have been sorted into octiles based on their most recent change in return on equity (dROE). The end of a fiscal quarter of a firm is required to be at most 6 months prior to portfolio formation. Monthly octile returns have been computed and portfolios are rebalanced on monthly basis.

3.5 Data Preparation

The monthly stock return data from CRSP from July year t to June (year t+1) has been merged with the annual accounting data of t-1 (where t is in years) for the anomalies that are based on annual accounting data. For the anomalies using quarterly data, the monthly stock returns from CRSP have been merged with the quarterly data of t-1 (where t is in quarters).

Whether to use lagged or contemporaneous ESG data is an open question for academics (Lioui, 2018b). Although ESG scores are measured on an annual basis, Refinitiv updates the ESG database throughout the year (Refinitiv, 2021b). To ensure that an ESG score of a certain company is known to a hypothetical investor at a certain moment in time, the lagged values reduce potential endogeneity and simultaneity problems (Oikonomou et al., 2014). For this reason, the choice has been made to merge the monthly stock return data from CRSP from July year t to June (year t+1) with the ESG data of t-1. This ensures that the values of which the predictions were made by a fictitious investor at a certain moment in time were known (also known as preventing look-ahead bias).

Duplicates have been dropped, as well as observations that were not available in all datasets. In addition, in case a company has two different share classes, but the same underlying fundamentals, e.g., ordinary shares and special voting rights, only the ordinary share class is kept in the database, while the other one is removed.

To ensure that the other concerning information was available to the market during the period being analyzed, the market capitalization has been lagged by one month, as well as the anomaly variable for the low volatility effect for both total and idiosyncratic volatility. The market capitalization is divided by 1000 to guarantee it is presented in millions, consistent with the accounting measures. Firms with a negative book equity (BE) are excluded since a firm's limited liability structure means that shareholders cannot have negative value, so exclusion makes sense since a negative BE is difficult to interpret. The inclusion of these firms with the method of sorting stocks into portfolios would result, especially for the value vs growth anomalies, that these stocks are being grouped into the lowest portfolio. This could result in an enhanced high-minus-low anomaly effect,

Table 3.2: *Composition of firms separated by divisions. The total amount of firms displayed (493) results from all necessary transformations regarding the data and after omitting firms or observations, due to missing data in one of the corresponding databases, or exclusionary practices mentioned in Section 3.2. No S&P 500 constituent can be grouped under the range of Standard Industrial Classification (SIC) codes that represent the division Public Administration.*

Composition of the Divisions	**% of total companies included**
1. Agriculture, Forestry and Fishing	2
2. Mining	10
3. Construction	5
4. Manufacturing	184
5. Transport, Communication, Electric, Gas	66
6. Wholesale Trade	19
7. Retail Trade	31
8. Finance, Insurance and Real Estate	88
9. Services	73
10. Public Administration	0
11. Non-Classifiable	15
Total	*493*

however, whether one could believe that these stocks have the highest growth potential or that these distressed firms should be classified differently is controversial (Brown et al., 2007). For this reason, this paper follows most academics and practitioners and excludes these observations.

In contrast to Fama and French (1992), not only common stocks with a share code of 10 and 11 are included. Since this research tries to capture a comprehensive view of how high vs low ESG scored constituents of the SP 500 vary in their anomaly performance, exclusion of stocks with a different share code than 10 or 11 would eliminate 51 constituents and any conclusion regarding the SP 500 would be misrepresenting the index. For this reason, there has been chosen to keep the composition of included divisions and their corresponding stocks within the SP 500 complete, as can be seen in *Table 3.2*.

Furthermore, the exclusion of financial firms in financial analysis is quite common and has been explained by Fama and French (1992). Financial firms' capital structure is largely influenced by their leverage, so comparing non-financial firms and financial firms could be cumbersome. However, in this research, financial firms have been included for most anomalies, for several reasons. Firstly, any conclusion regarding the index in case of excluding financial firms would lead to a misrepresentation of the SP500 index, since the removal of those firms would lead to exclusion of 63 constituents.

Secondly, limited research has focused on the impact of ESG scores on the returns in the financial sector, while investors also pay attention to the ESG commitments in this sector, which makes the inclusion of those firms meaningful to analyze. For instance, banks, in particular, are seen as one of the least female-friendly industries (O'Sullivan, 2021) and besides, they seem to perform consistently high on material ESG issues, while the opposite is found on immaterial issues[2]. Thirdly, and perhaps most importantly, for most of the investigated anomalies in this research, the extensive use of leverage in financial firms does not negatively influence the conventional method of sorting stocks into portfolios. This

[2]Immaterial ESG issues are considered to have no direct impacting a firm's financial performance, while material ESG issues consist of issues that are likely to affect the financial condition or operating performance of firms (Consolandi et al., 2020).

Table 3.3: *Number of stocks displayed per division that are included in each of the eight quantiles, sorted on Operating Leverage (OL). Separation is established based on their Standard Industrial Classification (SIC) codes as described in Table 3.2. Division 10 (Public Administration) has been excluded in the table since no firm included in the S&P 500 index can be grouped into that division. Observation.*

Operating Leverage	**US Stocks Grouped by Division**										
Portfolios	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	0	540	0	588	1.233	4	0	6.522	533	95	*9.515*
2	12	1.043	3	4.482	1.484	144	6	805	2.446	258	*10.683*
3	46	580	96	5.91	819	196	107	230	2.439	153	*10.576*
4	0	280	139	6.583	555	169	102	146	1.868	215	*10.057*
5	0	129	161	6.483	369	259	32	32	1.562	180	*9.207*
6	0	146	329	6.21	339	264	286	109	946	81	*8.710*
7	0	95	332	4.144	322	468	1.892	193	900	12	*8.358*
8	0	49	238	1.495	621	1.6	3.513	559	1.405	155	*9.635*
Total	*58*	*2.862*	*1.298*	*35.895*	*5.742*	*3.104*	*5.938*	*8.596*	*12.099*	*1.149*	*76.741*

statement has been tested by investigating the properties of the portfolios based on their SIC codes, for both main anomalies and their robustness checks, and can be found in the *Appendix*, *Tables 1-10.* Only in the case of the Operating Leverage anomaly, the inclusion of highly leveraged firms seems to be particularly prevalent in the bottom portfolio, as can be observed in *Table 3.3.* Here, division 8 is centralized in portfolio 1 and represents 68.5% of the total stocks included in the bottom portfolio.

Disregarding this concern would negatively influence the ability to compare non-financial and financial firms. Namely, including financial firms for the analysis of this anomaly would result in creating portfolios that effectively separate financial firms from non-financial firms, while this research pursues to separate firms based on their differences in fundamentals. For this reason, financial firms are included for all investigated anomalies, except for the intangibles anomaly category. Subsequently, this results in a lower number of observations for the operating leverage anomaly, compared to the other anomalies. As a result, the exclusion of financial firms raises again the concern of having too few stocks into double-sorted (83) portfolios to effectively diversify away most of the idiosyncratic risk, as discussed in *Section 3.2.* For this reason, the use of quintiles to construct a (53) double-sort has been used for this particular anomaly. The exclusion of financial firms for this anomaly has reduced the percentage of stocks characterized by division 8 from 68.5% to 18.9% in the bottom portfolio. An overview of how the divisions are divided in the case of quintiles is included in the *Appendix*, *Table A.6.*

The abovementioned transformations and the consequence of dropping observations that are missing in one of the databases, results in a final merged database of 493 firms, with 87.090 observations. The data has a time span of 16 years that starts from January 2005 to December 2020 in calendar years, with the fiscal years starting in 2004 and ending in 2019.

3.6 Descriptive Statistics

Table 3.4 summarizes the univariate statistic of the anomalies investigated in this research. As can be derived from the momentum strategies, the average formation period value of the alternative momentum (16.1%) strategy exceeds the formation value of the other two momentum strategies. This can be explained by the fact that it includes a longer formation period. Moreover, all the momentum strategies seem to contain a higher average momentum value and higher standard deviation among low ESG stocks.

Table 3.4: *The table depicts data on the S&P 500 constituents over 16 years, starting from 2005 until the end of 2020, showing for each anomaly variable the univariate Statistics (mean, standard deviation). The key anomalies are displayed, followed by the robustness tests performed in this research. Market capitalization is added to provide information regarding the size of the companies that contain a high- or low ESG rating. Besides, the lagged value will be used to construct value-weighted returns.*

SUMMARY STATISTIC						
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
	Full Sample Anomaly Return		***Sorted on High ESG***		***Sorted on Low ESG***	
Key Anomalies						
MOM	.1461	.2822	.1155	.2401	.1586	.2972
Total-VOL	.0782	.0387	.0708	.0336	.0819	.0392
OL	.7822	.6949	.7441	.6114	.7338	.6803
$_q$CFP	.0284	.0858	.028	.0505	.0274	.0517
dROE	-.0006	.5341	.0007	.8288	-.0009	.1779
Robustness Tests						
Novy-MOM	.0816	.213	.0636	.1851	.088	.2222
Alt-MOM	.161	.2902	.1283	.2504	.1796	.3096
Idio-VOL	.0669	.0333	.061	.0264	.0702	.0351
$_q$OCFP	.0729	.1659	.0749	.1567	.0669	.1291
ROE	.0568	1.2401	.0549	.5944	.0457	.1887
Market Cap	*30809.23*	*63207.39*	*58086.09*	*88563.69*	*17000.49*	*30700.98*

The volatility anomalies show both similar observations of having higher volatility among low ESG stocks. This suggests that these anomalies are highly correlated. The average ratio of operating leverage (.7822) in the entire sample surpasses the ratio of both high and low ESG stocks, which reveals that middlingly rated ESG stocks contain the highest operating leverage. Nevertheless, high ESG stocks seem to entail a slightly higher share of fixed costs than low ESG stocks.

Noteworthy, the average $_q$CFP for the entire sample is also higher than that of high or low ESG stocks. Furthermore, the fact that the mean value for $_q$OCFP (.0749) is higher for high ESG stocks, while this relation does not hold for the $_q$CFP anomaly may suggest that the $_q$OCFP is not an expanded value-glamour proxy as discussed in *Section 2.3.3*.

The average 4-quarter change in return on equity (dROE) is only positive among high ESG stocks, but also experiences the highest standard deviation compared to middlingly- and low ESG rated firms. The return on equity is higher among high ESG rated firms, compared to low ESG rated firms, however, the highest ROE is captured by mediocre ESG rated firms, since the mean ROE is higher for the entire sample. Lastly, the market capitalization reveals that high ESG rated companies are generally the largest companies, while the smallest firms are also rated the lowest. This may suggest that larger firms tend to be more active in ESG practices. This could be the result of capturing more (media) attention or simply because these firms have more resources to participate in ESG practices. Moreover, the observation that larger firms experience lower volatility might be explained that these firms are more diversified. Whether these distinctive features between high and low ESG stocks result in higher returns for investors that use these measures to construct their portfolios, will be discussed in *Chapter 4*.

3.7 Methodology and Testing Anomalies

In this section, the statistical methods used in this research will be discussed. For each anomaly, portfolios have been constructed following a single- and double-sorted approach. The single-sorted have been constructed to test the anomalies merely on the existence in this dataset, which helps to create a clearer picture of how the anomaly performance differs from high and low ESG stocks once the double-sorted portfolio returns are calculated. Moreover, this section also highlights the details of the used factor models to test if the found anomaly return can be explained by the risk factors included in the FF-3 and FF-5 models. The analysis for the factor models has been included in the *Appendix*.

Portfolio construction

For each anomaly investigated, a general anomaly value has been computed based on the corresponding trading strategy's formation period as defined in *Section 3.4*. Each anomaly value has been sorted and allocated to one of the eight octile portfolios, monthly rebalanced. It should be noted that some of the annual accounting variables (e.g., operating leverage) or quarterly accounting variables (e.g., quarterly (operating) cash flow) remain constant for 12 or 3 months respectively. To maintain comparable holding periods across different anomalies, the portfolio returns are therefore calculated and rebalanced every month. From a practical perspective, however, investors effectively rebalance every 3 months based on quarterly data and every 12 months on annual data.

The octile portfolios are formed based on New York Stock Exchange (NYSE) breakpoints, analogous to Fama French (1996). They explain their primary reason to prefer the use of NYSE breakpoints, against the alternative of using NYSE-AMEX-NASDAQ breakpoints, since the latter one would result in their research in microcaps accounting for more than 60% of the stocks in extreme deciles. This can be explained by the fact that the CRSP database included the AMEX and the NASDAQ exchanges in the database in a later period (1962 and 1972 respectively), while these stocks only accounted for 26.6% of the total market capitalization. This implied that these stocks were predominantly smaller compared to stocks listed on the NYSE. Hence, the magnitude of anomaly return can be largely influenced by these microcaps, particularly with the use of equal-weighting (Hou et al., 2020). Subsequently, if breakpoints were based on all considered stocks in the CRSP universe, portfolios would simply separate the AMEX, NASDAQ, and NYSE stocks, while NYSE breakpoints assign a fair amount of small and big stocks into the extreme quantiles. There should be noted, that this research focuses on the 500 largest companies, so the degree to which micro-cap firms would drive the anomaly returns does not apply to this context. Nevertheless, the analysis has been constructed based on NYSE-AMEX-NASDAQ breakpoints, and the smaller-cap firms within the index still resulted in an amplified anomaly return. Therefore, to guarantee the statistical reliability of the portfolio sorts in this paper, all single- and double-sorts have been constructed with NYSE breakpoints.

Each constructed portfolio has been complemented with the average holding return for that particular month, equally- and value-weighted. Each value-weighted return has been assigned based on the lagged market capitalization, to ensure this information was known to the market at the time of portfolio formation. The use of value weighting the returns as a robustness check aside from equal weighting, which most of the original papers apply, has been chosen since value-weighted returns reflects the portfolios held by mainstream, sophisticated longer-term investors (e.g., investment- and pension funds) (Humphrey et al., 2012). Apart from this, the statistical reliability of sorts with NYSE breakpoints in combination with value-weighted returns increased the economic importance considerably (Hou et al., 2020), and seem to decrease, sometimes even led to the disappearance of apparent anomalies in long-term post-event returns (Fama, 1998).

The high-minus-low portfolios are defined as the top octile (for a corresponding anomaly) minus the bottom octile (of that corresponding anomaly). This applies for all anomalies, except for the low volatility anomalies, since here the stocks are similarly ranked as all other anomaly values, based on the lowest value in the bottom octile and highest value in the highest octile, which is the opposite of how Blitz Vliet (2007) and Ang et al. (2006) performed their analyses. To meet their procedure, by construction, the high-minus-low portfolio is substituted with a low-minus-high portfolio.

Furthermore, to statistically test the hypotheses, the constructed high-minus-low portfolios under high and low ESG stocks will be used to create an additional portfolio that goes long in the HML high ESG portfolio and goes short in the HML low ESG portfolio, denoted as HMLhigh-minus-HMLlow. This provides information on whether the potential economically significant difference in return between the two portfolios is also statistically significant.

The difference between the top and bottom octile portfolio return, as well as the difference in long-short return of the HML portfolio return, will be tested with a t-test, applying Newey-west standard errors to adjust all t-values for autocorrelation and heteroscedasticity (Newey West, 1987). For every category anomaly, if at least one trading strategy of HMLhigh-minus-HMLlow under equal or value-weighted returns surpasses the significance level of at least 10%, the corresponding hypothesis will be rejected in favor of the alternative hypothesis.

This paper does not take transaction costs into account and does not calculate excess returns. The latter has to do with the fact that for calculating the long-minus-short portfolios, one deducts the risk-free rate for the long and short portfolios separately to calculate excess return. If subsequently, a long-minus-short portfolio has been constructed, the risk-free rate cancels out and thus does not influence the long-short portfolio return.

Lastly, as extra robustness tests besides the value-weighted returns and all robustness anomalies, the reliability of the results that are found under the double-sorted octile portfolio construction (83) will be evaluated by performing the analysis again under double-sorts based on quintiles (53). This is performed to test to what extent the choice of portfolio construction, and therefore the number of stocks included in the double-sorted portfolios, are driving the results. This may be the case in particular for the value-weighted double-sorted portfolios since the allocation of at least 12 stocks into portfolios could raise concerns about the extent to which sufficient idiosyncratic risk is diversified away. Besides, to confirm the earlier presumptions that financial firms are not driving the returns for the profitability anomalies, as some researchers find that ROE increases with more financial leverage (e.g. Ahsan, 2012), the profitability anomalies will be constructed as well under quintiles while excluding financial firms.

3.8 Testing Relative to Factor Models

After constructing all portfolios and calculating the corresponding returns, each anomaly will be tested relative to the CAPM, FF-3, and FF-5 model, to test whether the cross-sectional variation in return can be explained by the systematic risk factors. If an alpha remains significant even after controlling for the systematic factors in the corresponding risk models, it implies a statistically significant return that can be attributed to unsystematic or unpriced risk. In other words, testing it relative to a factor model exhibits if the considered trading strategy's return represents a distinct anomaly, or rather captures one of the factors in disguise. The results for these tests, as well as the underlying theories behind the models, are included in the *Appendix*.

Chapter 4

Empirical Results

In this section, the empirical results of the investigated anomalies will be discussed. First, the results will be discussed of the equal-weighted (EW) and value-weighted (VW) returns (single-sorts), subsequently, the double-sorted portfolio returns will be analyzed. After that, the returns on the long-short portfolio that goes long in the double-sorted high ESG portfolios and short in the double-sorted low ESG portfolios will be discussed, which will result in a concluding word concerning the hypotheses. Lastly, the multivariate regression results on the key anomalies (which are presented in the *Appendix*) show the anomaly returns regressed against the factor models.

4.1 Momentum Anomaly

Panel A to F of *Table 4.1* report the empirical results of the momentum trading strategies, taking all 493 firms into account. As can be observed in the high-minus-low (HML) column, the only significant momentum strategies are the intermediate momentum strategy of Novy-Marx (2012), with a value-weighted monthly return of 0.52% (t=1.99) and the alternative momentum strategy (t=1.94), which displays an equally weighted return 0.59% per month. The momentum strategy by Jegadeesh and Titman (1993) (panel A and B) not only lacks statistical significance but generates a negative return under NYSE-EW, which is inconsistent with the original paper.

These observations imply a diminishing predictive power of recent returns among the largest US stocks. The lack of statistical significance in this paper, especially for the original momentum strategy, may be explained by the fact that these large-cap stocks are generally more efficiently priced than smaller-cap stocks. This in turn hints towards excessively weighting on microcaps in the original paper which might explain the overstated monthly return of 1% that they found, regardless of the duration of the holding period. However, it may also be explained by disappearing momentum returns due to investors being aware of the existence of this anomaly after publication, resulting in exploiting the anomaly by arbitrating away the momentum returns based on recent information. The fact that Novy-Marx's momentum strategy performs a significant return, especially under NYSE-VW, is in line with previous literature since this strategy seems to perform the best among the largest, most liquid stocks.

Panel G-J refer to the original momentum strategy (1993), double-sorted on anomaly value and ESG scores. Again, no evidence is found of a significant effect. The underperformance of high ESG momentum portfolios under NYSE-EW returns might imply to be in line with the first hypothesis, however, the returns remain insignificant. Remarkably, under both NYSE-EW and NYSE-VW (panel G and I), the 8$^{\text{th}}$ average portfolio return for high ESG stocks generates consistently lower returns than the 7$^{\text{th}}$ octile portfolio. This demonstrates that in this dataset the extreme quantiles do not capture the highest return,

Table 4.1: *Displays the average returns of the eight portfolios based on Momentum (Mom), Novy-Momentum (Novy-Mom), and Alternative Momentum (Alt Mom) strategies. The HML column demonstrates the difference between the eighth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-F displays the return of the strategy regressed on the entire sample, while Panel G-R displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

MOMENTUM ANOMALIES										
	1	2	3	4	5	6	7	8	**HML**	**DIFF**
Panel A: Mom EW	.0153	.0128	.0127	.0117	.012	.0107	.0111	.0148	-.0005 (.0048)	
Panel B: Mom VW	.0089	.0098	.011	.0102	.0092	.009	.0095	.0108	.0018 (.0037)	
Panel C: Novy-Mom EW	.0138	.0123	.0123	.0115	.0111	.0128	.0124	.0147	.0009 (.0026)	
Panel D: Novy-Mom VW	.0076	.0078	.0098	.0094	.0092	.0095	.0119	.0127	**.0052**** **(.0026)**	
Panel E: Alt Mom EW	.0134	.0122	.0126	.0118	.012	.0121	.0121	.0146	**.0059*** **(.003)**	
Panel F: Alt Mom VW	.006	.0104	.0116	.0085	.0082	.0108	.0096	.0119	.0012 (.0033)	
Panel G: Mom EW HIGH ESG	.0121	.0125	.0116	.0112	.0108	.0086	.0099	.0091	-.0029 (.005)	-.0012 (.003)
Panel H: Mom EW LOW ESG	.0175	.014	.0124	.0097	.0122	.0099	.0147	.0158	-.0018 (.0057)	
Panel I: Mom VW HIGH ESG	.0072	.0091	.0109	.0105	.0094	.0084	.0103	.0089	.0017 (.0043)	.0032 (.0048)
Panel J: Mom VW LOW ESG	.0133	.0158	.0114	.0076	.0097	.0073	.0138	.0117	-.0016 (.0051)	
Panel K: Novy-Mom EW HIGH ESG	.0096	.0108	.0102	.0109	.0102	.0107	.0103	.0121	.0025 (.0036)	.0048 (.0041)
Panel L: Novy-Mom EW LOW ESG	.0169	.0135	.0121	.0108	.0135	.0128	.0142	.0145	-.0023 (.0037)	
Panel M: Novy-Mom VW HIGH ESG	.0057	.009	.0065	.0097	.0082	.0103	.0118	.0121	.0064 (.0042)	.0048 (.0041)
Panel N: Novy-Mom VW LOW ESG	.0122	.0123	.011	.0094	.0123	.0094	.0112	.0126	.0004 (.0036)	
Panel O: Alt Mom EW HIGH ESG	.0136	.0139	.0122	.014	.0104	.0136	.0133	.015	.0013 (.0035)	-.0001 (.0038)
Panel P Alt Mom EW LOW ESG	.0089	.0125	.0116	.0087	.0103	.0116	.0099	.0102	.0014 (.0049)	
Panel Q: Alt Mom VW HIGH ESG	.0039	.0092	.0119	.0077	.0063	.0113	.0102	.0118	**.0079*** **(.004)**	.0051 (.0055)
Panel R: Alt Mom VW LOW ESG	.0091	.0142	.009	.0106	.0114	.0108	.0106	.0119	.0027 (0.0045)	

which by itself explains the lower long-short portfolio return compared to panels A and B. This might suggest being in line with the first hypothesis that fewer speculators are involved among high ESG stocks to exploit the momentum anomaly, however, this cannot be established with certainty since it lacks statistical significance.

Panel K-N show the double-sorted average portfolio return of the intermediate momentum strategy. Noteworthy, despite a significant positive return under all stocks with

NYSE-VW (Panel D), Novy-Marx's momentum strategy becomes insignificant under the double-sorted portfolio for both high and low ESG rated stocks. The observation of higher average long-short portfolio return under value-weighted returns (panel M and N) compared to panel K and L, is again in line with the previous literature that more intermediate momentum return is captured by the larger and more liquid stocks. Nevertheless, since none of the coefficients surpass the threshold of at least 10% statistical significance, conclusions regarding the observations should be considered with cautiousness.

Panel O-R show the returns of the alternative momentum portfolios using a double-sort on momentum value and ESG scores. Panel Q displays a significant positive return of 9.48% annually (t=1.94) with NYSE-VW, which is economically significant. However, this observation is not in line with the first hypothesis that assumes to have more patient capital invested in high ESG stocks, since this would have led to speculators being more attracted towards low ESG stocks, which in turn would have resulted in an expected out-performance for low ESG stocks under the momentum strategy. Panel O does show an underperformance under high ESG stocks, however, the coefficient is not statistically significant. Since the alternative momentum strategy builds on the intermediate momentum strategy, it is not surprising to observe this particular momentum strategy to be more prevailing among value-weighted returns. Nonetheless, the outperformance among high ESG stocks, even though only significant at 10%, is unexpected. This implies that the minor evidence for a profitable momentum strategy among the largest US stocks is only obtained by creating portfolios with formation periods focusing on a longer time horizon, rather than basing one's formation period on the predictability of recent returns.

Lastly, by observing the long-short portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks and short the HML portfolio of low ESG stocks, displayed as DIFF in the last column of *Table 4.1*, one can observe that neither momentum strategy generates a return under high ESG stocks that is statistically different from the same strategy under low ESG stocks. To test the robustness of the results in lower quantiles, the same analysis has been performed based on quintiles instead of octiles and shows similar results of no compelling evidence for a significant momentum strategy. Notably, the statistical significance of the coefficients in panel D, E, and Q of *Table 4.1* become insignificant after using quintiles instead of octiles. This can be explained by the fact that the use of fewer quantiles results in capturing fewer extreme values of the distribution, consequently measuring a less extreme momentum effect. These results have been included in the *Appendix* and can be found in *Table A.19*.

Considering the empirical findings, this paper does not find enough evidence to conclude that the momentum strategy performs significantly differently under high ESG stocks than under low ESG stocks and thus rejects the first hypothesis that predicts outperformance under low ESG stocks. Nor is there found compelling evidence that the returns under low and high ESG scores show a predictable co-movement of stocks within the same momentum investment style. There can, however, be stated with caution that the longer time horizon momentum strategies seem to perform better among larger firms, which is consistent with previous literature. Since the coefficients under high and low ESG generally lack statistical significance, the empirical findings do not allow to distinguish between the potential rational or behavioral aspects separately or evaluate their relative performance. The absence of highly significant momentum returns among high and low ESG stocks, do however suggest that past returns no longer predict cross-sectional variation in stock returns, at least under these larger-cap stocks. This may imply that practitioners potentially acknowledged that these strategies were profitable and since publication arbitrated away these anomaly returns. This by itself implies that momentum anomaly returns are not as pervasive as Fama French (2008) conclude, but rather be apparent dependent on which dataset one uses.

4.2 Value-Glamour Anomaly

Table 4.2 reports the average returns of the eight portfolios and the HML portfolio, based on quarterly cash flow-to-price ($_{\mathrm{q}}$CFP) and its robustness test, the quarterly operating cash flow-to-price ($_{\mathrm{q}}$OCFP). As can be derived from panel A to D, the $_{\mathrm{q}}$OCFP anomaly is virtually non-existent. This can be observed by the long-short portfolios being insignificant. On the contrary, investing based on $_{\mathrm{q}}$CFP proofs to generate an average return over a 16-year period of around 5.64% to 6.84% annually (t=1.91 and 1.74), depending on whether one applies NYSE-EW or NYSE-VW portfolios respectively. These returns are economically significant, although smaller in magnitude than the estimates of Lakonishok et al. (1994) and Hou et al. (2020). This difference may be explained by the use of only larger-cap stocks within this dataset, or due to decreasing predictable power of value characteristics after investors became aware of the anomalies after publication. The observation of dissimilar portfolio returns between $_{\mathrm{q}}$CFP and $_{\mathrm{q}}$OCFP seems to confirm the earlier notion that $_{\mathrm{q}}$OCFP does not contribute to the belief of capturing one of the broadly published fundamental-to-price characteristics as Lakonishok et al. (1994) documented.

Panel E-H show the returns of the double-sorted portfolios based on $_{\mathrm{q}}$CFP and ESG scores. Remarkably, panel E and G show both highly economically and statistically significant returns for the average high ESG long-short portfolio. The NYSE-VW high-minus-low portfolio generates on average 11.28% (t=3.42) per annum, while NYSE-EW generates an average of 10.8% (t=2.88) annually. This is similar to the 11% annual return that Lakonishok et al. (1994) document, although it should be noted that they use NYSE-Amex breakpoints and EW returns with annual accounting measures. The observation of generating more return for the long-short portfolio with NYSE-VW under high ESG stocks than with NYSE-EW is striking since generally, equally-weighted returns show a larger magnitude than value-weighted returns, due to overweighting smaller-cap stocks. Besides, maybe more importantly, the average long-short portfolio return also surpasses the return of the original papers, this indicates strong evidence of a value anomaly among high ESG stocks and is robust under both equal and value-weighted return.

Moreover, panel H shows that trading based on $_{\mathrm{q}}$CFP among low ESG stocks also provided investors a return of 9.84% (t=2.06) annually, which is economically significant and statistically significant at 5%. The interpretation of why the value anomaly merely generates profits under low ESG stocks if one uses value-weighted returns, compared to equally weighted returns, may imply that value strategies in this dataset perform better among the largest-cap stocks.

Nevertheless, the outperformance of value strategies among high ESG stocks, both under NYSE-EW and NYSE-VW, is noticeable. By comparing Panel E and F, one can observe that the eight individual low ESG double-sorted portfolios generally perform better than the eight individual portfolios among high ESG stocks. The difference, however, between the most extreme portfolios is larger among high ESG stocks, which seems to explain the larger long-short spread generated under high ESG stocks. This may imply that also under high ESG stocks, investors have the tendency to follow naïve strategies or carry the irrational belief of perceiving a well-run company as being a good investment. This might explain why investors among high ESG stocks seem to invest in glamour stocks, consequently resulting in high ESG stocks with high cash flow-to-price (value stocks) becoming underpriced. This, in turn, might have to do with investors being generally aware that investing in high ESG rated companies is associated with rather long-term value creation than short-term value creation since it costs time and resources for a firm to align their commitment with their ESG objectives. Consequently, investors might carry the irrational belief that mostly well-run companies (glamour stocks) will succeed in this ambition and thus are willing to overpay for glamour stocks and therefore provide low average return going forward, while leaving the value stocks (portfolio 8) underpriced,

Table 4.2: *Displays the average returns of the eight portfolios based on Quarterly Cash flow-to-price ($_qCFP$) strategies and its robustness test the Quarterly operating cash flow-to-price ($_qOCFP$). The HML column demonstrates the difference between the eighth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-D displays the return of the strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <.10, ** p <.05, *** p <0.01.*

QUARTERLY (OPERATING) CASH FLOW ANOMALIES										
	1	2	3	4	5	6	7	8	**HML**	**DIFF**
Panel A: $_q$CFP EW	.0125	.0119	.012	.0131	.0133	.0129	.0157	.0182	**.0057*** **(.003)**	
Panel B: $_q$CFP VW	.0092	.0086	.0097	.0108	.0109	.0089	.0128	.0139	**.0047*** **(.0027)**	
Panel C: $_q$OCFP EW	.0125	.0126	.0131	.0127	.0129	.0128	.0149	.0164	.004 (.0026)	
Panel D: $_q$OCFP VW	.0083	.0098	.0102	.0092	.0101	.0121	.0117	.0104	.0021 (.0027)	
Panel E: $_q$CFP EW HIGH ESG	.0076	.0086	.0107	.0091	.0124	.0111	.013	.0166	**.0090***** **(.0026)**	**.0050*** **(.0027)**
Panel F: $_q$CFP EW LOW ESG	.0133	.0126	.014	.0163	.0142	.0148	.0171	.0172	.0039 (.0039)	
Panel G: $_q$CFP VW HIGH ESG	.0065	.0077	.0095	.0103	.0107	.0073	.0116	.016	**.0094***** **(.0033)**	.0013 (.0029)
Panel H: $_q$CFP VW LOW ESG	.0099	.0096	.0133	.0143	.0139	.0107	.0124	.0181	**.0082**** **(.004)**	
Panel I: $_q$OCFP EW HIGH ESG	.0103	.0095	.0105	.01	.0111	.0108	.0133	.0126	.0023 (.0023)	-.0028 (.0032)
Panel J: $_q$OCFP EW LOW ESG	.012	.014	.015	.015	.014	.015	.015	.017	.005 (.0039)	
Panel K: $_q$OCFP VW HIGH	.0071	.0079	.0094	.0083	.0102	.0119	.011	.0099	.0029 (.0033)	-.0041 (.0034)
Panel L: $_q$OCFP VW LOW	.007	.013	.013	.012	.012	.011	.013	.014	.007 (.0048)	

providing high average return going forward.

This intuition is not in line with the earlier notion that ESG investors carry the same underlying mentality of value investors, which was built on the belief that both investment strategies require a long time horizon to systematically pay off. The findings rather point towards the idea that ESG investors which prioritize ethical values, also follow naïve strategies. Whether this can be explained by overreacting to good or bad news or extrapolating past earnings too far ahead or carry an irrational belief of perceiving a well-run company with a good investment, cannot be determined by observing the empirical findings in this paper.

This paper does, however, find evidence that value strategies with NYSE-EW under high ESG rated stocks perform statistically and economically different from value strategies under low ESG rated stocks. This can be observed by the last column in panel E and F, where the return of the portfolio is given that goes long in the HML portfolio of high

ESG stocks and short the HML portfolio of low ESG stocks (HML^{high}-minus-HML^{low}). The return of 6% on annual basis with a t-statistic of 1.85, is economically significant and inconsistent with the null hypothesis of no difference in return. Albeit, the difference in HML^{high}-minus-HML^{low} becomes insignificant under the same portfolio with NYSE-VW (column DIFF, panel G and H). Taken together these observations, this paper does find evidence of a statistically (and economically) significant return difference between value strategies under high and low ESG rated stocks. Therefore, the third hypothesis that states no difference will be rejected.

Moreover, when analyzing the value strategies by using quintiles, as can be observed in *Table A.20* in the *Appendix*, the coefficients show comparable results with respect to equal-weighted returns under the double sorted HML portfolio, although the returns are smaller in magnitude. This implies that the $_q$CFP anomaly is not only persistent when creating portfolios based on the highest and lowest 12.5% of the distribution, although the use of quintiles results in capturing fewer extreme values. The latter might explain why the double-sorted value-weighted portfolios lose some explanatory power when using fewer quantiles, as well as resulting in the DIFF portfolios becoming insignificant.

Lastly, Panel I-L again provide no evidence that trading on $_q$OCFP predicts a positive significant return. Nor does it contribute to the belief that $_q$OCFP is an extended value-glamour proxy, since variation in return between high and low ESG rated stocks are not in line with what trading on $_q$CFP predicts, as Desai et al. (2004) documented.

4.3 Profitability Anomaly

In *Table 4.3*, the average one-month holding return of the eight portfolios based on dROE and ROE are displayed. In panel A to D, one can observe the octile portfolio returns using all 493 stocks. Remarkably, all long-short portfolio returns display highly significant results, implying that these anomalies are far from exploited and that investors can earn a positive abnormal return by trading on a simple accounting measure, without extensive fundamental analysis. Investing based on dROE generates an octile high-minus-low return of 1% (EW) and 1.28% (VW) per month (t=5.15 and 5.4 respectively). In line with Hou et al. (2020), investing based on dROE seems to outperform investing based on ROE. This holds for both NYSE-EW and NYSE-VW returns. However, inconsistent with their paper, VW returns are higher than EW returns, implying that the largest companies have accounted for an unusually high proportion of returns, which means that investors seem to be better off applying value-weighted allocation in case of single-sorted portfolios based on these profitability measures.

In panel E to H, the average one-month holding return for the portfolios double-sorted on ESG and dROE are displayed and report both lower returns than using a single-sorted portfolio based on dROE (panel A and B), this holds for both low- and high ESG stocks. Consequently, using a double-sort on dROE and the middlingly rated ESG stocks, one would earn a higher return, namely, this would result in a high-minus-low portfolio return of 1.68% per month (t=4.52) with NYSE-VW and 1.24% monthly (t=5.04) with NYSE-EW. This is an interesting observation since this means that even though high ESG stocks contain on average the highest positive yearly change in dROE (*Section 3.6*; summary statistics), trading on dROE is not as effective of a return predictor for high ESG stocks compared to middlingly rated ESG stocks. This suggests that even though improved margins are a sound sign for a firm to generate funds internally, it does not by definition mean higher returns for investors.

Panel I to L show the double sorted portfolios based on ESG and ROE. Remarkably, under ROE, the double-sorted portfolios show under this accounting-based ratio that for low and high ESG stocks both with NYSE-EW and NYSE-VW, returns of the long-short

Table 4.3: *Displays the average returns of the eight portfolios based on the 4-quarter change in Return on Equity (dROE) and its robustness check the pure Return on equity (ROE) anomaly. The HML column demonstrates the difference between the eighth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-D displays the return of the strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

FOUR QUARTER CHANGE IN RETURN ON EQUITY ANOMALIES (dROE)										
	1	2	3	4	5	6	7	8	**HML**	**DIFF**
Panel A: dROE EW	.0092	.0089	.0103	.0107	.0121	.0146	.0161	.0191	**.0100*** (.0019)**	
Panel B: dROE VW	.0024	.0054	.0074	.0085	.0105	.0111	.0134	.0152	**.0128*** (.0024)**	
Panel C: ROE EW	.0097	.0114	.0122	.0117	.0115	.0146	.0151	.0159	**.0062** (.0025)**	
Panel D: ROE VW	.0021	.0069	.0104	.0087	.0078	.011	.0109	.0133	**.0111*** (.003)**	
Panel E: dROE EW HIGH ESG	.0072	.0067	.0078	.008	.0112	.0129	.0137	.0151	**.0079*** (.0023)**	-.0021 (.0048)
Panel F: dROE EW LOW ESG	.0095	.0109	.0097	.0118	.0131	.0162	.0166	.0194	**.0100*** (.0029)**	
Panel G: dROE VW HIGH ESG	.002	.0049	.0057	.0067	.0112	.0105	.0131	.0131	**.0110*** (.0033)**	.0017 (.0048)
Panel H: dROE VW LOW ESG	.0049	.0067	.0067	.01	.012	.013	.0146	.0143	**.0093** (.004)**	
Panel I: ROE EW HIGH ESG	.006	.0063	.0107	.0114	.0074	.012	.013	.0141	**.0081** (.0032)**	-.001 (.0042)
Panel J: ROE EW LOW ESG	.0079	.0146	.0126	.0123	.0113	.0152	.0172	.0169	**.0091** (.0036)**	
Panel K: ROE VW HIGH ESG	.0008	.0032	.0089	.0091	.0046	.0104	.0099	.0135	**.0127*** (.0034)**	.0012 (.0042)
Panel L: ROE VW LOW ESG	.0018	.0127	.0121	.0142	.0094	.0127	.0145	.0133	**.0115*** (.0041)**	

portfolios are strictly higher than the average return of the entire sample (panel C and D). This is opposite to the findings of dROE and highlights that even though both anomalies are closely related, their predictive power of return differs substantially. What the trading strategies do have in common, as shown in panel K and G, is that under high ESG stocks, value-weighted returns are higher than low ESG stocks. This observation also holds for a (53) double-sort, as can be observed in *Table A.21* (*Appendix*). This highlights that larger-cap firms perform better under high ESG stocks. The opposite is the case for returns with NYSE-EW, where low ESG stocks seem to outperform high ESG stocks, as shown in panel F and J.

Two important observations with respect to the individual portfolios for both dROE and ROE is that almost all individual portfolios under low ESG stocks, seem to outperform the same individual portfolio under high ESG stocks. This is interesting since *Section 3.6* (summary statistics) displayed that high ESG stocks on average, contain higher positive values for both dROE and ROE. This implies that even though high ESG stocks generally provide more return on equity, trading on firms that tend to generate more profit for their shareholders does not by definition provide more return for investors. The second noteworthy observation is that the findings are in line with the fundamental investment theory. This can be observed by the increasing rate of return from portfolio 1 to portfolio 8. This theory predicts that firms with higher profit measures are a proxy for growth predictors (Hou et al., 2021), which means that higher expected investment growth (portfolio 8) should earn more return than firms with low expected investment growth (portfolio 1). This might explain why the portfolios load negatively and are highly significant on the value premium, as can be observed in *Table A.13* in the *Appendix*, which indicates that the portfolios behave more like a growth stock portfolio. This is related to the findings of Hou et al. (2015), who find that the investment factor would play an important role in explaining the value factor.

Furthermore, the observations in the last column, displayed as DIFF, do not imply a statistically, nor economically significant return. The HML^{high}-minus-HML^{low} portfolio under dROE generates an annual return of -2.52% (t=-0.63) with NYSE-EW and 2.04% (t=0.36) with NYSE-VW. These results are of similar magnitude under ROE. Hence, despite the prevailing reliability that these profitability anomalies generate, no clear significant difference has been found between low and high ESG rated stocks. This is also the case when performing the analysis by dividing the data into 5 equal parts, which can be found in the *Appendix*, *Table A.21*. An interesting observation with respect to the (53) double-sort, is that high ESG stocks strictly earn more return than the double-sorted portfolios under low ESG stocks. However, the differences in return of the HML^{high}-minus-HML^{low} portfolio remain insignificant. For this reason, this paper does not find enough evidence to reject the null hypothesis of no difference in return by following profitability strategies among high or low ESG rated stocks.

Lastly, by observing *Table A.22* of the *Appendix*, one can derive the findings of the analysis under fifths but excluding financial firms. These findings confirm that the returns generated by trading strategies based on dROE and ROE are not driven by financially levered firms, nor does it change the conclusion with respect to statistical different returns between the HML^{high}-minus-HML^{low} portfolios.

4.4 Intangibles Anomaly

Panel A and B of *Table 4.4*, details the average monthly holding returns of the quintile portfolios sorted on operating leverage (OL). The high-minus-low portfolio earns an average return of 0.41% per month (t=2.81) with NYSE-EW, and 0.43% per month (t=2.34) with NYSE-VW. Hence, this paper finds evidence that stocks of firms with leveraged assets (in terms of operating leverage and not financial leverage), significantly outperform firms with unlevered assets. This is consistent with the operating leverage hypothesis that expects firms with higher fixed costs in proportion to their total assets to earn a higher average return.

The findings are closely related to the findings of Novy-Marx (2012) since he found an average monthly return of 0.51% and 0.44% for NYSE-EW and NYSE-VW respectively. Nevertheless, this paper finds a higher return for value-weighted portfolios, which is inconsistent with the original paper. This difference may be explained by the fact that the original paper uses a dataset that included micro-cap stocks, which is seen to strengthen the size premium in the OL portfolios (Novy-Marx, 2012).

Panel C to F show the monthly holding period return of the double-sorted portfolios on both OL and ESG scores. Strikingly, the OL anomaly is only prevailing among high

Table 4.4: *Displays the average returns of the five portfolios based on the Operating Leverage (OL) anomaly. The HML column demonstrates the difference between the fifth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-B displays the return of the strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

OPERATING LEVERAGE ANOMALIES							
	1	2	3	4	5	**HML**	**DIFF**
Panel A: OL EW	.0106	.0133	.0136	.0144	.0147	**.0041*** (.0014)**	
Panel B: OL VW	.0071	.0105	.0111	.012	.0114	**.0043** (.0018)**	
Panel C: OL ESG EW HIGH ESG	.007	.0103	.0111	.0125	.0123	**.0053*** (.0019)**	**.0039* (.0023)**
Panel D: OL ESG EW LOW ESG	.013	.0133	.0141	.0164	.0144	.0014 (.0018)	
Panel E: OL ESG VW HIGH ESG	.0063	.0097	.0103	.0099	.0113	**.0051** (.0025)**	**.0050* (.0029)**
Panel F: OL ESG VW LOW ESG	.0108	.0124	.0121	.0139	.0108	.0000 (0.0022)	

ESG stocks, this holds for both EW and VW returns. Besides, the long-short portfolio quintile return seems to be enhanced among the double-sorted portfolios compared to the single-sorted OL portfolios. This suggests that the operating leverage anomaly seems to play a more prominent role among high ESG rated firms and creates greater trading opportunities for investors. Specifically, investors trading on the OL anomaly within high ESG stocks, enhance their annual return from 5.28% to 6.36% (t=2.8) with NYSE-EW and from 5.16% to 6.12% (t=2.03) with NYSE-VW, compared to the basic scenario of using all 493 firms (panel A and B). This is both economically and statistically significant.

The enlarged HML return under high ESG rated firms is mostly driven by the strikingly lower return that is generated by portfolio 1 in panel C and E. This may imply, in line with Novy Marx's hypothesis, that under high ESG rated stocks, firms that contain low operating leverage are significantly less risky. If the findings are interpreted purely from the perspective of the operating leverage hypothesis, the observed lower returns for all high ESG rated firms, relative to the returns of the low ESG rated firms, may reflect that low ESG rated stocks are overall perceived riskier than high ESG rated stocks. This makes sense from the perspective of ESG since high ESG rated firms already meet the growing interest of investors by scoring well on the several ESG dimensions. However, in combination with operational flexibility, the risk associated with industry shocks may become less problematic for high ESG rated firms, compared to low ESG rated firms. This has to do with the notion that low ESG rated firms in general still need to improve their ESG commitments to meet investors growing demand for ESG practices, while ESG practices are associated with increasing levels of fixed costs (Perez-Batres et al., 2012).

This would suggest that low ESG rated stocks, with low operating leverage, are perceived riskier than high ESG rated stocks with low operating leverage. Hence, this could explain the smaller spread between the long-short portfolio of low ESG rated firms, compared to high ESG rated firms. This may also explain the higher return of quintile 5 in panel D, compared to the average fifth quintile portfolio return of high ESG rated firms (panel C).

Moreover, while low ESG rated firms need to invest considerably to earn a higher ESG score, Novy-Marx (2011) highlights that firms with high operating leverage invest considerably less than firms with low operating leverage, which makes levered firms (OL) with low ESG scores thus even riskier. Besides, Novy-Marx states that this effect is stronger when measured on an equally weighted basis, which could explain why one observes that the fifth quintile portfolio return under NYSE-EW in panel C and D is both higher than the fifth quintile portfolio return under NYSE-VW in panel E and F.

The central question by observing the empirical findings, not confined to only the operating leverage anomaly, is why these returns can persist over several years. A potential economic explanation might be that limited operational flexibility is highly related to the value premium. Namely, Zhang (2005) illustrates that increased operating leverage leads to a higher value premium. This has been tested and is indeed the case. The results of the multivariate regression results for OL regressed against the CAPM, FF-3, and FF-5 model can be found in the *Appendix*, *Table A.14*. Fama French (1996) explain that the value premium may persist since a contraction, as a result of a negative shock to a firm's prospects, is likely more correlated with a reduction in human capital for a distressed firm than for a less distressed firm. Consequently, investors working in those firms may be reluctant to hold these stocks, leaving the value premium intact. Since the value premium is thus closely related to limited operational flexibility, this might be an explanation for why these returns have persisted for so long.

Furthermore, the last column of *Table 4.4* displays the return of the portfolio that takes a long position in the high-minus-low portfolio of high ESG stocks, while shorting the high-minus-low portfolio of low ESG stocks. As can be observed, both portfolios under NYSE-EW and NYSE-VW generate an economically significant monthly return of 0.39% (t=1.73) and 0.5% (t=1.68) respectively. For this reason, this paper finds enough evidence to reject the fourth hypothesis that trading on the operating leverage anomaly results in similar returns for both high and low ESG stocks.

4.5 Trading Friction Anomaly

Panel A – D of *Table 4.5*, displays the average one month holding period return of the eight single-sorted portfolios on the total volatility strategy by Blitz Vliet (2007) in Panel A and B, and on the idiosyncratic volatility by Ang et al. (2006) in Panel C and D.

Panel A and B show that the low-minus-high (LMH) octile portfolio earns on average -1.21% per month (t=-2.75) with NYSE-EW and -0.84% (t=-1.71) with NYSE-VW. This is remarkable since the negative coefficient for both anomalies implies a positive risk premium on volatility being priced in, which is inconsistent with the original papers. Both anomalies are significant at 1% under NYSE-EW. The empirical findings of this paper show that the volatility effect is still prevailing, although in the last 16 years the effect seems to become negative. It may be that after the low volatility anomaly was published in fall 2007, investors came aware of the investment strategy and arbitrated away the opportunity to generate similar returns of that of the market, but at a systematically lower level of risk. Nevertheless, this paper does not find evidence for that. Regressing the returns in the subsample starting from 2003 until fall 2007 (time of publication), resulted in an average one-month holding LMH return of -1.39% (t=-2.56) for total volatility with NYSE-EW and -.97% (t= -1.47) with NYSE-VW. Although it should be noted that this subsample is relatively short to base a conclusion on it, these findings in combination with panel A and B are surprisingly inconsistent with the original papers.

The inconsistency might be explained by a different sample period of the documented papers, implying that the volatility effect is most prominent in the first 20 years starting from 1980. The negative LMH coefficient may also imply that the potential explanation by Black (1972), namely, that the outperformance of low volatility stocks persists because of borrowing restrictions, has weakened over time. The use of larger-cap stocks is not expected to explain the difference, since Blitz Vliet (2007) also used a large-cap universe. Moreover, the use of weekly returns to assess volatility increases the effect of noise trading on volatility and could therefore amplify the long-short portfolio return, which could be a potential explanation for the observed inconsistency. Lastly, the findings are in line with Bali Cakici (2008), who only find a persistent negative cross-sectional relation between risk and return among small stocks, in the absence of using NYSE breakpoints. This again highlights the statistical reliability of the used methodology in this paper.

Panel E – L of *Table 4.5* show the one-month holding return of the double-sorted portfolios based on ESG and total volatility (panel E-H), and ESG and idiosyncratic volatility (panel I-L). Two observations stand out. Firstly, the low volatility anomaly is merely present among low ESG stocks but report a negative LMH portfolio return. This holds for both investigated volatility anomalies. Secondly, the average return per portfolio that high ESG stocks earn sorted on volatility, as well as the long-short spread, generates an overall lower return than low ESG stocks. This is inconsistent with the prediction of Liou (2018b) since he predicts an outperformance of high ESG stocks based on the volatility anomaly. However, in his prediction, he did not account for a positive risk-return relationship. What this may imply, concerning his reasoning, is that investors do not account for larger firms being more harmful to the environment by pricing in the enlarged ESG exposure.

What the findings do suggest is that price efficiency varies between high and low ESG stocks, as profit opportunities appear to be persistent only among low ESG stocks. This may have to do with a rational explanation in line with the thoughts of Merton (1987), that exclusionary practices among low ESG stocks result in more price inefficiency compared to the broadly popular investments of higher ESG rated stocks. In addition to this, high ESG rated firms receive more institutional ownership and besides more analyst coverage (Dhaliwal et al., 2011). Consequently, less analyst coverage among low ESG stocks may imply slower dissemination of new information, which could also contribute to the higher price inefficiency among these stocks. Besides, the ability for larger firms to dedicate more resources to reporting, enforces the enhanced price inefficiency among low ESG rated stocks (which tend to be smaller in size, as seen in *Section 3.6*) to the extent that it affects the reputation and the cost of capital (Boffo Patalano, 2020). Lastly, Ang et al. (2006) provide a potential explanation for their observed low volatility effect, namely, that the difference in return between high and low idiosyncratic volatility stocks can be explained by the amounts of private information that these stocks contain. Their reasoning builds upon the notion that stocks with more private information demand higher expected returns. In line with the earlier potential explanations regarding the greater commitment of larger companies to report more sophisticated, it could potentially explain why this anomaly is amplified and appears to be persistent only among low ESG rated stocks.

From a practical view, to benefit from the slightly higher inefficiencies among low ESG rated stocks, investors should then trade against the traditional way of constructing an LMH volatility portfolio to exploit the volatility anomaly, by going long in the highest volatile stocks, while shorting the lowest volatile stocks. According to panel F, this would generate a return of 10,8% annually (t=2.62) with NYSE-EW. This is larger in magnitude than using NYSE-VW, which would have resulted in a less, but still economically and statistically significant average return of 8.4% per year (t=1.91).

Lastly, to state whether the observed return differences are indeed inconsistent with the hypothesis of similar returns, the portfolio return of a portfolio that takes a long position in the LMH portfolio of high ESG stocks, while shorting the LMH portfolio of low ESG stocks, is displayed as DIFF in the last column of *Table 4.5*. The results show that only the DIFF portfolios under idiosyncratic risk with NYSE-EW and NYSE-VW surpass the significance level of 10% (t=1.82 and t=1.67 respectively). The analysis under quintiles, as can be observed in *Table A.23* of the *Appendix*, show similar results, although a less strong short-long portfolio effect for the value-weighted portfolio under idiosyncratic volatility, which can be explained by the lower cut point to divide stocks into portfolios.

Since this paper finds that the idiosyncratic volatility strategy produces different returns among high and low ESG stocks, where the difference between the LMH^{high}-minus-LMH^{low} portfolio return surpasses at least 10% significance level, this paper finds enough evidence to reject the null hypothesis of no difference in return.

Table 4.5: *Displays the average returns of the eight portfolios based on Total Volatility (VOL) and its robustness test Idiosyncratic Volatility (IDIO-VOL). The LMH column demonstrates the difference between the first portfolio and the eight portfolios, the significance of the LMH return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the LMH portfolio of high ESG stocks while going short in the LMH portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-D displays the return of the single-sorted strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

LOW VOLATILITY ANOMALIES										
	1	2	3	4	5	6	7	8	**LMH**	**DIFF**
Panel A: VOL EW	.0088	.01	.0109	.0108	.0115	.0133	.0133	.0208	**-.0121***** **(.0044)**	
Panel B: VOL VW	.0077	.0083	.0097	.0093	.0094	.0118	.0122	.0161	**-.0084*** **(.0049)**	
Panel C: IDIO-VOL EW	.0112	.0113	.0102	.0107	.0118	.0117	.0126	.0199	**-.0086***** **(.0031)**	
Panel D: IDIO-VOL VW	.0097	.0105	.0075	.0076	.0102	.0106	.0098	.0144	-.0047 (.0037)	
Panel E: VOL EW HIGH ESG	.0088	.0102	.0104	.0093	.0111	.0108	.0112	.0162	-.0074 (.0052)	.0034 (.0031)
Panel F: VOL EW LOW ESG	.0104	.0101	.011	.0118	.009	.0148	.0148	.0211	**-.0108***** **(.0041)**	
Panel G: VOL VW HIGH ESG	.0081	.0087	.009	.0086	.0092	.0082	.0117	.0136	-.0056 (.0054)	.0015 (.0042)
Panel H: VOL VW LOW ESG	.0106	.0076	.0106	.0079	.0084	.0145	.0144	.0177	**-.0070*** **(.0037)**	
Panel I: IDIO-VOL EW HIGH ESG	.0112	.0106	.0103	.0093	.0101	.0102	.0098	.0148	-.0036 (.0048)	**.0064*** **(.0035)**
Panel J: IDIO-VOL EW LOW ESG	.0108	.0118	.0116	.0113	.0124	.0113	.0133	.0208	**-.0100***** **(.0032)**	
Panel K: IDIO-VOL VW HIGH ESG	.0099	.01	.008	.0067	.0098	.0113	.0079	.0108	-.0008 (.005)	**.0069*** **(.0041)**
Panel L: IDIO-VOL VW LOW ESG	.0097	.0109	.009	.0099	.0103	.0101	.0121	.0174	**-.0077**** **(.0033)**	

Chapter 5

Conclusion

In this paper, I aimed at answering the following research question: *To what extent do stock market anomalies behave differently among high-rated ESG stocks and low-rated ESG stocks in the SP500 index?* By investigating trading strategies among 5 different category anomalies using data from January 2005 until December 2020, I find no compelling evidence that returns under low and high ESG rated stocks show predictable co-movement within the same momentum investment style, which indicates that past returns no longer predict cross-sectional variation in stock returns under the SP 500 constituents.

With respect to value strategies, this paper finds slight evidence of more pronounced value strategies among high ESG rated stocks, where the difference between high and low ESG stocks is statistically significant at 10%. This observation is consistent with the interpretation that ESG investors might carry the irrational belief that mostly well-run companies are more likely to succeed in the ambition of aligning their ESG aspirations with successful implementation. This might explain why investors are willing to overpay for glamour stocks, while leaving value stocks underpriced.

When attempting to understand profitability anomalies, I find that the investigated profitability measures show to be effective return predictors, but no significant distinction is found that high expected investment growth among high ESG stocks produces more significant returns than low ESG rated stocks.

By analyzing differences in operational flexibility between sustainable and less sustainable stocks, I discover an enhanced anomaly return among high ESG rated stocks, where the difference with low ESG rated stocks is statistically significant at 10% for both equal and value-weighted returns.

Lastly, with respect to trading friction anomalies, this paper finds a positive risk premium on volatility being priced in, where profit opportunities based on low volatility anomalies appear to be persistent only among low ESG rated stocks. When trying to exploit variation in the short-long portfolio returns between high and low ESG rated stocks double-sorted on volatility, investors produce significant return differences only when trading on idiosyncratic volatility.

I consider this paper as a step forward towards a more profound understanding of how trading strategies differ between stocks with distinct characteristics. Moreover, this research sheds new light on the controversy of efficient markets since trading opportunities arise even in the presence of the 500 largest constituents of the SP 500 index. This research does not find a one-sided understanding that merely high or low ESG stocks are more susceptible for anomalies in general, but rather exhibit distinctive results among the anomalies. This leaves several avenues for further research. For instance, to what extent can behavioral finance help to explain the differences in price inefficiencies among high and low ESG rated stocks, since ESG investing highlights that investment decisions are influenced by nonpecuniary motivations. In addition, to what extent is the use of ESG scores exacerbating price inefficiencies, since the low correlation between different data providers suggests that financial markets have difficulties in pricing in ESG performance efficiently. These avenues, among others, would help to understand what drives cross-sectional differences in returns among high and low ESG stocks, and more importantly, they will help answer if one can expect these differences to persist into the future. I would like to encourage further investigation on what drives the differences in stock market anomalies within the same investment style, to enhance a deeper understanding of these phenomena, and to help investors design more lucrative trading strategies, even if ethical principles restrict one's potential universe of stocks.

Chapter 6

Limitations

In this section, I would like to address some of the limitations of this research.

The first limitation is related to the objectivity of the information that is used to evaluate ESG aspects. Even though the use of secondary data is convenient for both investors and academics, the different methodologies that third parties use for measuring ESG performance among different firms raise the concern that the outcomes of research lack validity when using different data providers (Berg et al., 2019). An ESG rating is therefore susceptible to biases or methodological errors since it is dependent on the way it is constructed, but it also lacks credibility since the information reported by firms lack clear guidelines or the verification as to how and to what extent in detail it should be reported (L. Chen et al., 2016). This makes it crucial for investors to be cautious when making investment decisions based solely on ESG scores. Besides, academics should know the differences between the distinctive methodologies among the data providers, to understand what data conforms more to one educational or research purpose. These conflicting aspects also contribute to the idea of why ESG investing may enhance market inefficiency. Some even predict that behavioral anomalies are now supplemented with sustainability anomalies (Schoenmaker Schramade, 2019).

Besides, the use of one numerical ESG score provides a useful overview of a firm's ESG performance, but the empirical findings do not distinguish between the relative importance of the several aspects considered. This makes it also challenging to interpret investors' potential underlying beliefs when observing return differences. The findings in this paper do not allow us to distinguish to what extent the relative impact of nonpecuniary investment motivations is amplifying returns for some of the investigated anomalies or to which dimension of the ESG they conform the most. Stock prices are prone to many different factors, so conclusions in the light of ESG should be treated with caution.

Lastly, although the use of large-cap stocks in relation to anomaly testing is not a limitation by definition, as the 500 largest US companies are considered to be efficiently priced as they receive more analyst coverage (Dhaliwal et al., 2011), but one should be careful by inferring any conclusions within this paper to smaller- or even micro-cap stocks.

Chapter 7

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Appendix A

Appendix

Table A.1-3: *Number of stocks displayed per division that are included in each of the eight quantiles, sorted on Momentum (Jegadeesh and Titman (1993), Novy-Marx's Momentum strategy (2012), and the alternative Momentum strategy constructed to test a longer time horizon. The separation of stocks is based on their Standard Industrial Classification (SIC) codes as presented in Table 3.2. Division 10 (Public Administration) has been excluded in the table since no firm included in the S&P 500 index can be grouped into that division.*

	US stocks grouped by division										
Mom portfolios	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	9	610	266	4.422	1.449	296	813	2.042	1.485	142	*11.534*
2	2	340	117	3.971	1.473	324	660	2.36	1.251	78	*10.576*
3	9	264	128	3.919	1.64	394	531	2.355	1.243	62	*10.545*
4	10	236	87	3.923	1.625	396	515	2.342	1.345	65	*10.544*
5	10	201	115	4.038	1.605	403	538	2.339	1.459	90	*10.798*
6	3	236	101	4.052	1.498	408	542	2.298	1.545	99	*10.782*
7	4	284	117	4.296	1.476	405	721	2.087	1.772	137	*11.299*
8	0	523	295	5.32	1.421	310	1.146	1.736	2.549	349	*13.649*
Total	*47*	*2.694*	*1.226*	*33.941*	*12.187*	*2.936*	*5.466*	*17.559*	*12.649*	*1.022*	*89.727*

	US stocks grouped by division										
Novy-Mom Portfolios	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	Total
1	5	587	254	4.513	1.467	314	851	1.96	1.648	151	*11.75*
2	5	324	124	4.08	1.535	322	638	2.31	1.341	82	*10.761*
3	7	254	114	3.905	1.593	403	558	2.407	1.325	88	*10.654*
4	14	229	99	4.029	1.577	394	543	2.355	1.331	84	*10.655*
5	7	226	96	4.068	1.614	381	568	2.301	1.376	90	*10.727*
6	3	234	129	4.026	1.559	429	586	2.293	1.542	94	*10.895*
7	5	295	167	4.173	1.486	406	684	2.139	1.705	125	*11.185*
8	1	545	243	5.21	1.408	287	1.071	1.794	2.427	312	*13.298*
Total	*47*	*2.694*	*1.226*	*34.004*	*12.239*	*2.936*	*5.499*	*17.559*	*12.695*	*1.026*	*89.925*

	US stocks grouped by division										
Alt- Mom portfolios	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	10	595	263	4.244	1.377	272	781	1.958	1.439	140	*11.079*
2	2	306	123	3.958	1.446	306	668	2.241	1.176	72	*10.298*
3	10	260	124	3.733	1.551	392	521	2.264	1.263	50	*10.168*
4	9	225	94	3.76	1.57	327	516	2.272	1.314	63	*10.15*
5	11	205	93	3.836	1.516	440	507	2.284	1.376	80	*10.348*
6	4	215	111	3.981	1.522	409	515	2.248	1.471	101	*10.577*
7	1	308	123	4.09	1.443	381	686	1.978	1.672	116	*10.798*
8	0	500	259	5.128	1.327	328	1.09	1.739	2.459	314	*13.144*
Total	*47*	*2.614*	*1.19*	*32.73*	*11.752*	*2.855*	*5.284*	*16.984*	*12.17*	*936*	*86.562*

Table A.4-5: *Number of stocks displayed per division that are included in each of the eight quantiles, sorted on total volatility and idiosyncratic volatility. The separation of stocks is based on their Standard Industrial Classification (SIC) codes as described in Table 3.2. Division 10 (Public Administration) has been excluded in the table since no firm included in the S&P 500 index can be grouped into that division.*

						US stocks grouped by division					
VOL	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	0	17	2	2.746	2.859	319	267	1.611	559	40	*8.42*
2	0	22	24	2.843	1.913	510	439	2.116	960	38	*8.865*
3	0	62	31	3.506	1.245	512	625	2.006	1.298	34	*9.319*
4	0	112	54	3.859	1.084	348	623	2.196	1.321	65	*9.662*
5	15	247	165	3.914	1.043	321	676	2.312	1.363	84	*10.14*
6	21	415	147	3.965	904	314	741	2.018	1.689	58	*10.272*
7	11	542	285	4.057	935	277	842	2.061	1.553	112	*10.675*
8	0	1.041	410	5.516	959	78	702	1.537	2.514	351	*13.108*
Total	*47*	*2.458*	*1.118*	*30.406*	*10.942*	*2.679*	*4.915*	*15.857*	*11.257*	*782*	*80.461*

						US stocks grouped by division					
IDIO	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	0	20	2	3.564	964	537	203	2.635	1.069	41	*9.035*
2	12	73	11	3.485	1.326	477	333	2.139	1.095	62	*9.013*
3	21	50	51	3.366	1.586	487	475	2.078	965	4	*9.083*
4	7	82	90	3.153	1.936	306	553	1.89	999	29	*9.045*
5	2	152	119	3.386	1.763	303	674	1.953	1.296	91	*9.739*
6	5	336	163	3.914	1.17	268	780	1.944	1.482	60	*10.122*
7	0	563	360	3.994	1.177	204	1.036	1.782	1.788	87	*10.991*
8	0	1.182	322	5.544	1.02	97	861	1.436	2.563	408	*13.433*
Total	*47*	*2.458*	*1.118*	*30.406*	*10.942*	*2.679*	*4.915*	*15.857*	*11.257*	*782*	*80.461*

Table A.6: *Number of stocks displayed per division that are included in each of the five quantiles, sorted on Operating leverage. The separation of stocks is based on their Standard Industrial Classification (SIC) codes as described in Table 3.2. Division 10 (Public Administration) has been excluded in the table since no firm included in the S&P 500 index can be grouped into that division.*

						US stocks grouped by division					
OL 5	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	12	1.53	3	4.801	2.684	146	18	2.879	2.851	322	*15.246*
2	46	796	163	9.198	1.067	260	149	142	3.529	265	*15.615*
3	0	228	219	9.681	686	366	77	62	2.386	314	*14.019*
4	0	224	570	8.631	478	424	771	73	1.415	93	*12.679*
5	0	84	343	3.584	827	1.908	4.923	5	1.918	155	*13.747*
Total	*58*	*2.862*	*1.298*	*35.895*	*5.742*	*3.104*	*5.938*	*3.161*	*12.099*	*1.149*	*71.306*

Table A.7-8: *Number of stocks displayed per division that are included in each of the eight quantiles, sorted on quarterly CFP and quarterly OCFP. The separation of stocks is based on their Standard Industrial Classification (SIC) codes as described in Table 3.2. Division 10 (Public Administration) has been excluded in the table since no firm included in the S&P 500 index can be grouped into that division.*

	US stocks grouped by division										
CFP	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	16	204	106	6.289	1.129	347	779	1.302	4.04	361	*14.573*
2	11	250	49	5.022	701	589	806	971	1.851	199	*10.449*
3	10	206	43	4.603	677	600	883	882	1.405	89	*9.398*
4	7	232	67	4.059	941	406	781	1.087	1.145	105	*8.83*
5	2	268	66	3.435	1.523	337	678	1.188	919	88	*8.504*
6	*0*	*352*	*69*	*2.808*	*2.083*	*174*	*612*	*1.203*	*738*	*46*	8.085
7	0	523	69	2.342	2.642	190	431	1.232	616	32	*8.077*
8	0	503	70	2.797	2.794	130	244	594	834	57	*8.023*
Total	*46*	*2.538*	*539*	*31.355*	*12.49*	*2.773*	*5.214*	*8.459*	*11.548*	*977*	*75.939*

	US stocks grouped by division										
OCFP	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	10	187	149	5.812	587	466	751	1.17	2.419	196	*11.747*
2	14	234	66	5.379	433	512	605	825	2.032	164	*10.264*
3	15	224	50	5.187	577	523	730	735	1.673	126	*9.84*
4	7	243	55	4.873	858	389	858	733	1.613	172	*9.801*
5	0	318	69	3.768	1.602	373	952	1.013	1.458	134	*9.687*
6	0	414	39	2.548	2.565	191	671	1.188	945	84	*8.645*
7	0	483	54	1.928	2.984	212	389	1.203	699	62	*8.014*
8	0	435	57	1.86	2.884	107	258	1.592	709	39	*7.941*
Total	*46*	*2.538*	*539*	*31.355*	*12.49*	*2.773*	*5.214*	*8.459*	*11.548*	*977*	*75.939*

Table A.9-10: *Number of stocks displayed per division that are included in each of the eight quantiles, sorted dROE, and ROE. The separation of stocks is based on their Standard Industrial Classification (SIC) codes as described in Table 3.2. Division 10 (Public Administration) has been excluded in the table since no firm included in the S&P 500 index can be grouped into that division.*

					US stocks grouped by division						
dROE	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	3	504	151	3.835	945	181	368	985	1.389	196	*8.557*
2	15	400	95	2.941	1.174	300	394	1.381	1.136	107	*7.943*
3	3	205	103	2.59	1.543	269	464	1.62	1.014	72	*7.883*
4	0	162	59	2.274	1.862	363	540	1.73	905	43	*7.938*
5	6	189	51	2.536	1.928	276	594	1.587	1.058	42	*8.267*
6	*12*	*272*	*89*	*2.623*	*1.57*	*312*	*606*	*1.444*	*1.062*	*39*	*8.029*
7	2	353	188	3.394	1.183	256	608	1.267	1.237	90	*8.578*
8	6	356	129	3.838	951	247	561	916	1.432	201	*8.637*
Total	*47*	*2.441*	*865*	*24.031*	*11.156*	*2.204*	*4.135*	*10.93*	*9.233*	*790*	*65.832*

					US stocks grouped by division						
ROE	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	*Total*
1	17	733	214	3.232	2.201	103	196	1.465	1.349	283	*9.793*
2	9	336	126	2.045	2.506	80	119	2.045	720	129	*8.115*
3	12	274	114	2.349	2.184	113	244	2.154	703	68	*8.215*
4	12	358	93	2.803	1.734	233	371	1.991	957	51	*8.603*
5	5	349	108	3.481	1.196	467	649	1.554	1.461	68	*9.338*
6	0	220	114	4.22	941	413	739	1.186	1.465	48	*9.346*
7	0	167	88	4.483	728	519	1.036	1.205	1.688	131	*10.045*
8	0	186	137	4.28	624	450	1.189	572	2.024	187	*9.649*
Total	*55*	*2.623*	*994*	*26.893*	*12.114*	*2.378*	*4.543*	*12.172*	*10.367*	*965*	*73.104*

Cross-Sectional Return Differences Explained by Risk Factors

In this section, the double-sorted anomaly returns are regressed against the systematic risk factors included in the CAPM model and the Fama French three- and five models. By regressing the returns on the corresponding risk factors, it provides a clearer picture of which factors load significantly on the double-sorted portfolio returns and thus offers a more profound analysis of what the properties of the double-sorted portfolios are and which underlying stocks they include. Before interpreting the results of these models, first will be explained what the factor models explain and how they are constructed.

Starting with the CAPM model, as described by Sharpe (1964), which captures the linear relationship between the expected return of an asset and the systematic risk of the market. Even though the model only captures one systematic risk factor (that of the market), the model articulates some key concepts. The CAPM model, as shown below, predicts a positive linear relationship between the return of the market and the expected return of the concerned stock, which is denoted as $R_{i,t}$. Beta (β_i) captures the co-movement of a stock's return and that of the market. The market risk premium ($RM_t - RF_t$), is the difference between the expected return of the market minus the risk-free rate. The error term is denoted as $\epsilon_{i,t}$.

$$R_{i,t} - RF_t = \alpha_i + \beta_i \, (RM_t - RF_t) + \epsilon_{i,t}$$

In 1993, Fama & French developed the three-factor model. This model consists of estimating asset expected return through its the expected risk premium linear relationship with the market expected risk premium, combined with adding two new factors to the single-factor model, namely, small-minus-big (SMB) and the high-minus-low (HmL) factor. These factors are the size- and value factors, which are based on the fact that small firms tend to outperform large firms and that value firms tend to outperform growth firms respectively. The two added factors tend to add explanatory power to the cross-sectional differences in return and extends the CAPM model to the following model:

$$R_{i,t} - RF_t = \alpha_i + \beta_i \, (RM_t - RF_t) + s_i \, SMB_t + h_i \, HmL_t + \epsilon_{i,t}$$

The introduction of the added factors improves the explanatory power of the model by reducing the alpha. This is a return that cannot be explained by one of the systematic risk factors. The 5-factor model has been introduced by Fama & French in 2015. The two academics again did an attempt to enhance explanatory power by adding two new factors, namely the profitability factor (RMW) and the investment factor (CMA). The robust-minus-weak (RMW), captures the difference between the returns of high and low operating profitability. The conservative-minus-aggressive (CMA) is based on the idea that high investing firms underperform relative to fewer investing firms. The expansion towards a 5-factor model resulted in the following equation:

$$R_{i,t} - RF_t = \alpha_i + \beta_i \, (RM_t - RF_t) + s_i \, SMB_t + h_i \, HmL_t + r_i \, RMW_t + c_i \, CMA_t + \epsilon_{i,t}$$

Fama & French (2015) state that the FF-5 model operates better in explaining the cross-section of average returns since the expansion of the FF-3 model significantly reduces the alpha (α_i) resulting in less unsolved anomalies. Like the other regressions, return differences between the top and bottom octiles have been estimated using Newey-West standard errors to correct for heteroscedasticity and autocorrelation.

Table A.11-15 displays the return characteristics of the constructed double-sorted trading strategies, together with the factor loadings and intercepts from the time-series regressions of the HML portfolio returns (LMH for volatility), which are regressed against the CAPM-model and the multifactor models (FF-3 and FF5). Consequently, this examines whether the raw returns found in sections 4.1-4.5 are driven by its exposure to common systematic risk factors included in the factor models.

Table A.11 displays the multivariate regression results for the momentum anomaly among high and low ESG stocks. Based on the regression intercepts, none of the double-sorted portfolios based on ESG and momentum generate a statistically significant return that can be attributed to unsystematic or unpriced risk. This is in line with the earlier findings in *Section 4.1*. By observing the highly significant coefficients for excess market return, one can infer that the equal-weighted double-sorted top-bottom portfolios seem to load strongly on the market, particularly among high ESG rated stocks, implying that the constructed double-sorted momentum portfolios among low ESG stocks are diversified well relative to market risk. The negative and highly significant HML coefficients both captured in the FF-3 and FF-5 model, indicate a negative relationship with the value premium, suggesting that the portfolios perform more as one with exposure to a growth stock portfolio, rather than exposure to value stocks. The constantly increasing R^2 among the factor models reveals a growing explanatory power when more systematic risk factors are included, indicating that around 22.6% of the variation in high ESG portfolio return is explained by the risk factors included in the FF-5 model.

Table A.12 shows the multivariate regression results for the $_{q}$CFP and displays that after controlling for the risk factors, the intercepts under the high ESG stocks remain highly significant, which confirms the earlier findings of *Section 4.2*. HmL and RMW, both significant at least at 5% in the FF-5 model, seem to explain a decent variation of the portfolio's return under high ESG stocks, sorted on $_{q}$CFP. By observing the adjusted-R2, around 13% of the variation is explained by the 5 factors. Moreover, the positive significant relationship with HmL and RMW indicates that the double-sorted portfolio has exposure to the value- and profitability premium, suggesting that the double-sorted portfolio tills towards value and profitable stocks. The former one is not surprising, as $_{q}$CFP is a value strategy, the latter, however, suggests that the portfolios under high ESG stocks include more profitable firms than the same sort under low ESG stocks. Another interesting observation is that the explained variation is higher under low ESG stocks. Here, 16.6% of the variation in return is explained by the 5 factors. Lastly, the significantly positive CMA coefficient among low ESG stocks seems to make HmL redundant under the FF-5 model, compared to the FF-3 model.

Table A.13 displays how the portfolio's return, double-sorted on dROE and ESG loads on the risk factors. Under both low and high ESG rated stocks, the double-sorted portfolio seems to move in the opposite direction of that of the market, although the magnitude is relatively small. The relatively low adjusted R2 among the models, seem to confirm the observation of few risk factors being statistically significant in describing the return of the double-sorted portfolio. The risk-adjusted alphas are highly significant (both statistically and economically) for both high and low double-sorted portfolios. This is in line with the earlier findings of *Section 4.3*. Remarkably, the dROE portfolio's return does not seem to be explained by the RMW factor, which is surprising, since its definition both seem to capture profitability commonality. The significant HmL factor is somewhat inconsistent with Fama & French (2015), who state that when profitability and investment factors are included in the FF-3 model, HmL seems to become redundant. The significant loading on the HmL factor is in line with earlier findings of (Hou et al., 2015), which state that investment factor suggests to play a similar role in factor regressions as HmL since both factors are highly correlated.

Table A.14 shows the extent to which the operating leverage portfolio is explained by the factor loadings. Notably, even after controlling for the systematic risk factors, the intercept coefficients still show an unexplained significant return for the high ESG rated firms of 0.49%, 0.55%, and 0.43% per month, for the CAPM, FF-3, and FF-5 model respectively. This is in line with the earlier findings of *Section 4.4*. By observing the relationship of the coefficients between the models, a few things stand out. First, the OL portfolio return seems to be far away from being explained by the market excess return, both on statistical and economical grounds. Besides, the high significant SMB coefficient among low ESG stock in both Fama French factor models is in line with the findings of Novy-Marx (2011) and may indicate that the portfolios double-sorted on low ESG rating and OL, capture mostly relatively smaller S&P500 firms than the high ESG rated stocks. This should be noted with caution, however, since the explanatory power of the risk factors is low, as observed by the low adjusted-R2. Besides, as Chen & Bassett (2014) explain, a positive SMB coefficient does not always have to imply that the portfolio weights towards smaller-cap stocks. Moreover, the HmL coefficient is merely significant among high ESG stocks, and it is consistent with the predictions of Zhang (2005) that the operating leverage anomaly tends to load significantly on the value premium. Furthermore, the highly significant RMW coefficient implies that on annual basis, 6% of the double-sorted portfolio return can be explained by the fact that these high ESG stocks seem to be more profitable.

Table A.15 reports how much variation in the low volatility low-minus-high portfolio returns can be explained by the common risk factors of the factor models. For all factor models, the risk-adjusted return on the volatility strategy is largely attributable to the risk factors in the factor models. In particular, the market risk factor seems to explain lots of the variation in return for both high and low ESG rated portfolios. Besides, all volatility portfolios seem to be negatively correlated with the market factor. Strikingly, almost all risk factors in the FF-5 model are significant among low ESG stocks, nevertheless, the low volatility strategy seems to generate a monthly average risk-adjusted return of -0.64%, which is economically significant. One can benefit from this by constructing a portfolio that trades against the low volatility anomaly. This is in line with the findings of *Section 4.5*. Furthermore, the highly significant negative SMB loadings may be interpreted that the portfolios weights towards large-cap stocks. The high adjusted-R2 stands out and implies that up to 55.4% of the variation in return is explained by the risk factors, this could explain the high significant explanatory power of almost all risk factors. Remarkably, the HmL coefficient is merely significant among high ESG stocks, whereby the negative beta suggests that the portfolio with high ESG stocks behaves more as a growth portfolio.

The multivariate regression results have also been regressed against the factor models using value-weighted returns and are included further in the *Appendix*, *Table A.16* to *Table A.18*. Also under NYSE-VW, the long-short double-sorted portfolio returns show similar findings.

Table A.11: *Displays the multivariate regression results of the momentum anomaly return regressed against the CAPM, Fama-French-3 factor model, and Fama-French-5 factor model. Each regression denotes the average monthly return for the double-sorted high-minus-low octile portfolio (under NYSE-EW) based on momentum and ESG scores. Each coefficient is stated with its Newey West standard deviation. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01. Adjusted-R2 is stated to indicate the percentage of variance in the dependent variable (momentum anomaly) that the independent variables (systematic risk factors) collectively explain.*

Momentum Anomaly	**CAPM**		**FF-3**		**FF-5**	
	LOW	HIGH	LOW	HIGH	LOW	HIGH
MKT ($R_m - R_f$)	-.0025*	-.0058***	-.0010	-.0043***	-.0013	-.0040***
	(.0014)	(.0020)	(.0011)	(.0014)	(.0011)	(.0014)
SMB			-.0011	-.0005	-.0017	-.0013
			(.0023)	(.0024)	(.0027)	(.0027)
HML			-.0076***	-.0081***	-.0061***	-.0092***
			(.0018)	(.0016)	(.0023)	(.0017)
RMW					-.0011	-.0016
					(.0034)	(.0028)
CMA					-.0046	.0047
					(.0048)	(.0056)
Intercept (α)	.0001	.0016	-.0032	-.0019	-.0024	-.0019
	(.0054)	(.0045)	(.0060)	(.0046)	(.0054)	(.0046)
Adjusted R^2	.0237	.1337	.1192	.2257	.1193	.2263

Table A.12: *Displays the multivariate regression results of the Quarterly Cash flow-to-price anomaly return regressed against the CAPM, Fama-French-3 factor model, and Fama-French-5 factor model. Each regression denotes the average monthly return for the double-sorted high-minus-low octile portfolio (under NYSE-EW) based on* $_q$*CFP and ESG scores. Each coefficient is stated with its Newey West standard deviation. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01. Adjusted-R2 is stated to indicate the percentage of variance in the dependent variable (*$_q$*CFP anomaly) that the independent variables (systematic risk factors) collectively explain.*

$_q$CFP Anomaly	**CAPM**		**FF-3**		**FF-5**	
	LOW	HIGH	LOW	HIGH	LOW	HIGH
MKT ($R_m - R_f$)	.0003	.0010	.0000	.0002	.0041	.0003
	(.0008)	(.0009)	(.0008)	(.0007)	(.0033)	(.0007)
SMB			-.0024**	.0004	-.0019	.0012
			(.0011)	(.0010)	(.0012)	(.0010)
HML			.0052**	.0042**	.0035	.0049**
			(.0021)	(.0019)	(.0022)	(.0020)
RMW					.0026*	.0055***
					(.0015)	(.0017)
CMA					.0059**	-.0028
					(.0023)	(.0027)
Intercept (α)	.0037	.0082***	.0055	.0100***	.0041	.0086***
	(.0043)	(.0030)	(.0034)	(.0024)	(.0033)	(.0020)
Adjusted R^2	-.0039	.0076	.1239	.0873	.1655	.1305

Table A.13: *Displays the multivariate regression results of the four-quarter change in Return on Equity (dRoe) anomaly return regressed against the CAPM, Fama-French-3 factor model, and Fama-French-5 factor model. Each regression denotes the average monthly return for the double-sorted high-minus-low octile portfolio (under NYSE-EW) based on dROE and ESG scores. Each coefficient is stated with its Newey West standard deviation. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01. Adjusted-R2 is stated to indicate the percentage of variance in the dependent variable (dROE anomaly) that the independent variables (systematic risk factors) collectively explain.*

dROE Anomaly	**CAPM**		**FF-3**		**FF-5**	
	LOW	HIGH	LOW	HIGH	LOW	HIGH
MKT ($R_m - R_f$)	-.0022**	-.0026*	-.0020*	-.0024**	-.0022**	-.0021**
	(.0010)	(.0014)	(.0010)	(.0010)	(.0010)	(.0010)
SMB			.0018	.0010	.0018	.0009
			(.0016)	(.0014)	(.0018)	(.0016)
HML			-.0041***	-.0029*	-.0032**	-.0040*
			(.0015)	(.0016)	(.0014)	(.0021)
RMW					.0005	-.0011
					(.0022)	(.0016)
CMA					-.0032	.0041
					(.0030)	(.0033)
Intercept (α)	.0117***	.0100***	.0103***	.0089***	.0104***	.0088***
	(.0027)	(.0021)	(.0030)	(.0024)	(.0028)	(.0026)
Adjusted R^2	.0339	.0762	.0665	.1008	.0699	.1078

Table A.14: *Displays the multivariate regression results of the operating leverage anomaly return regressed against the CAPM, Fama-French-3 factor model, and Fama-French-5 factor model. Each regression denotes the average monthly return for the double-sorted high-minus-low quintile portfolio (under NYSE-EW) based on operating leverage and ESG scores. Each coefficient is stated with its Newey West standard deviation. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01. Adjusted-R2 is stated to indicate the percentage of variance in the dependent variable (operating leverage anomaly) that the independent variables (systematic risk factors) collectively explain.*

OL Anomaly	**CAPM**		**FF-3**		**FF-5**	
	LOW	HIGH	LOW	HIGH	LOW	HIGH
MKT ($R_m - R_f$)	.0018**	.0000	.0009	-.0000	.0010	.0000
	(.0007)	(.0006)	(.0008)	(.0007)	(.0007)	(.0006)
SMB			.0027***	-.0010	.0030***	-.0003
			(.0008)	(.0013)	(.0009)	(.0012)
HML			.0010	.0018***	.0013	.0027***
			(.0011)	(.0007)	(.0008)	(.0007)
RMW					.0022	.0050***
					(.0020)	(.0012)
CMA					-.0010	-.0033**
					(.0029)	(.0016)
Intercept (α)	.0024	.0049**	.0032	.0055***	.0027	.0043**
	(.0029)	(.0020)	(.0027)	(.0021)	(.0030)	(.0021)
Adjusted R^2	.0345	-.0053	.0623	.0109	.0561	.0734

Table A.15: *Displays the multivariate regression results of the low (total) volatility anomaly return regressed against the CAPM, Fama-French-3 factor model, and Fama-French-5 factor model. Each regression denotes the average monthly return for the double-sorted low-minus-high octile portfolio (under NYSE-EW) based on the low (total) volatility and ESG scores. Each coefficient is stated with its Newey West standard deviation. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01. Adjusted-R2 is stated to indicate the percentage of variance in the dependent variable (low (total) volatility anomaly) that the independent variables (systematic risk factors) collectively explain.*

Volatility Anomaly	**CAPM**		**FF-3**		**FF-5**	
	LOW	HIGH	LOW	HIGH	LOW	HIGH
MKT ($R_m - R_f$)	-.0077***	-.0119***	-.0064***	-.0098***	-.0056***	-.0089***
	(.0009)	(.0014)	(.0007)	(.0014)	(.0007)	(.0011)
SMB			-.0080***	-.0066***	-.0072***	-.0059***
			(.0018)	(.0021)	(.0018)	(.0019)
HML			.0013	-.0044**	.0011	-.0051**
			(.0018)	(.0021)	(.0020)	(.0022)
RMW					.0043**	.0046
					(.0021)	(.0029)
CMA					.0049**	.0056
					(.0023)	(.0034)
Intercept (α)	-.0045	.0023	-.0046	-.0005	-.0064**	-.0025
	(.0033)	(.0042)	(.0031)	(.0037)	(.0031)	(.0039)
Adjusted R^2	.3423	.4808	.4235	.5403	.4426	.5542

Table A.16: *Displays the multivariate Value Weighted regression results of the corresponding anomalies regressed against the Factor five model. Each portfolio. Each regression denotes the average monthly return for the double-sorted high-minus-low octile portfolio (under NYSE-VW). Only the operating leverage strategy reflects the double-sorted high-minus-low quintile portfolio return. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

FF-5 VW	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	VW Mom HIGH	**VW Mom LOW**	**VW VOL HIGH**	**VW VOL LOW**	**VW OL HIGH**	**VW OL LOW**	**VW $_q$CFP HIGH**	**VW $_q$CFP LOW**	**VW dROE HIGH**	**VW dROE LOW**
Mkt-RF	-.0033**	-.0007	-.0080***	-.0049***	-.0011**	.0025***	-.0002	-.0002	-.0019**	-.0026***
	(.0014)	(.0011)	(.0014)	(.0009)	(.0005)	(.0007)	(.0008)	(.0008)	(.0008)	(.0009)
SMB	.0003	-.0017	-.0022	-.0046***	.0003	.0036***	.0016	-.0024*	.0023*	.0023
	(.0020)	(.0028)	(.0019)	(.0016)	(.0013)	(.0010)	(.0013)	(.0014)	(.0012)	(.0018)
HML	-.0101***	-.0073***	-.0051*	.0043*	.0017	.0006	.0068***	.0031	-.0050*	-.0049***
	(.0019)	(.0022)	(.0029)	(.0023)	(.0014)	(.0011)	(.0025)	(.0020)	(.0027)	(.0018)
RMW	.0021	-.0017	.0104**	.0082***	.0083***	.0021	.0052**	.0032	.0023	.0048
	(.0031)	(.0031)	(.0044)	(.0021)	(.0017)	(.0019)	(.0024)	(.0026)	(.0021)	(.0031)
CMA	.0034	-.0025	.0103***	.0081***	-.0043*	-.0002	-.0049*	.0081**	.0064*	.0010
	(.0056)	(.0046)	(.0037)	(.0030)	(.0022)	(.0025)	(.0027)	(.0033)	(.0038)	(.0026)
α	.0009	-.0028	-.0027	-.0029	.0036*	-.0006	.0100***	.0088**	.0107***	.0087**
	(.0037)	(.0051)	(.0046)	(.0027)	(.0019)	(.0026)	(.0024)	(.0035)	(.0027)	(.0037)

Table A.17: *Displays the multivariate Value Weighted regression results of the corresponding anomalies regressed against the Factor three model. Each portfolio. Each regression denotes the average monthly return for the double-sorted high-minus-low octile portfolio (under NYSE-VW). Only the operating leverage strategy reflects the double-sorted high-minus-low quintile portfolio return. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

FF-3 VW	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	VW Mom HIGH	**VW Mom LOW**	**VW VOL HIGH**	**VW VOL LOW**	**VW OL HIGH**	**VW OL LOW**	**VW $_q$CFP HIGH**	**VW $_q$CFP LOW**	**VW dROE HIGH**	**VW dROE LOW**
Mkt-RF	-.0038**	-.0005	-.0095***	-.0061***	-.0013*	.0024***	-.0001	-.0010	-.0025**	-.0030***
	(.0015)	(.0010)	(.0021)	(.0013)	(.0007)	(.0007)	(.0008)	(.0010)	(.0011)	(.0010)
SMB	.0006	-.0010	-.0038*	-.0064***	-.0011	.0035***	.0005	-.0032**	.0019*	.0016
	(.0017)	(.0024)	(.0023)	(.0018)	(.0012)	(.0011)	(.0013)	(.0013)	(.0011)	(.0018)
HML	-.0092***	-.0083***	-.0026	.0059***	.0005	.0011	.0056**	.0049***	-.0029	-.0043***
	(.0016)	(.0018)	(.0028)	(.0021)	(.0011)	(.0011)	(.0023)	(.0017)	(.0019)	(.0016)
Constant	.0019	-.0036	.0015	.0004	.0057***	.0001	.0111***	.0106***	.0120***	.0103***
	(.0032)	(.0055)	(.0045)	(.0030)	(.0021)	(.0022)	(.0025)	(.0038)	(.0031)	(.0038)

Table A.18: *Displays the multivariate Value Weighted regression results of the corresponding anomalies regressed against the Capital Asset Pricing Model (CAPM). Each portfolio. Each regression denotes the average monthly return for the double-sorted high-minus-low octile portfolio (under NYSE-VW). Only the operating leverage strategy reflects the double-sorted high-minus-low quintile portfolio return. LOW and HIGH corresponds to Low- and high ESG rated stocks. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

CAPM VW	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	VW Mom HIGH	**VW Mom LOW**	**VW VOL HIGH**	**VW VOL LOW**	**VW OL HIGH**	**VW OL LOW**	**VW $_q$CFP HIGH**	**VW $_q$CFP LOW**	**VW dROE HIGH**	**VW dROE LOW**
Mkt-RF	-.0053**	-.0021	-.0107***	-.0063***	-.0014*	.0033***	.0010	-.0008	-.0026*	-.0034***
	(.0021)	(.0013)	(.0020)	(.0011)	(.0007)	(.0007)	(.0009)	(.0009)	(.0014)	(.0010)
Constant	.0058	.0000	.0031	-.0019	.0056**	-.0008	.0087**	.0088**	.0130***	.0119***
	(.0039)	(.0049)	(.0047)	(.0031)	(.0022)	(.0024)	(.0035)	(.0042)	(.0036)	(.0039)

Table A.19: *Displays the average returns of the HML portfolios based on Momentum (Mom), Novy-Momentum (Novy-Mom), and Alternative Momentum (Alt Mom) strategies and the difference. The HML column demonstrates the difference between the fifth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-F displays the return of the strategy regressed on the entire sample, while Panel G-R displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

	HML	DIFF
Panel A: Mom EW	-.0006 (.0039)	
Panel B: Mom VW	.0004 (.0034)	
Panel C: Novy-Mom EW	.0009 (.0023)	
Panel D: Novy-Mom VW	.0039 (.0026)	
Panel E: Alt Mom EW	.0005 (.0029)	
Panel F: Alt Mom VW	.0032 (.0025)	
Panel G: Mom EW HIGH ESG	-.0040 (.0040)	-.0037 (.0024)
Panel H: Mom EW LOW ESG	-.0004 (.0047)	
Panel I: Mom VW HIGH ESG	-.0000 (.0037)	.0012 (.0037)
Panel J: Mom VW LOW ESG	-.0012 (.0044)	
Panel K: Novy-Mom EW HIGH ESG	.0007 (.0028)	.0013 (.0028)
Panel L: Novy-Mom EW LOW ESG	-.0006 (.0029)	
Panel M: Novy-Mom VW HIGH ESG	.0046 (.0033)	.0034 (.0030)
Panel N: Novy-Mom VW LOW ESG	.0013 (.0027)	
Panel O: Alt Mom EW HIGH ESG	-.0004 (.0032)	.0003 (.0029)
Panel P: Alt Mom EW LOW ESG	-.0007 (.0039)	
Panel Q: Alt Mom VW HIGH ESG	.0049 (.0032)	.0058 (.0043)
Panel R: Alt Mom VW LOW ESG	-.0008 (.0038)	

Table A.20: *Displays the average returns of the HML portfolios based on Quarterly Cash flow-to-price ($_q$CFP) strategies and its robustness test the Quarterly operating cash flow-to-price ($_q$OCFP). The HML column demonstrates the difference between the fifth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-D displays the return of the strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

	HML	**DIFF**
Panel A: $_q$CFP EW	**.0056****	
	(.0028)	
Panel B: $_q$CFP VW	.0043	
	(.0028)	
Panel C: $_q$OCFP EW	.0038	
	(.0026)	
Panel D: $_q$OCFP VW	.0021	
	(.0025)	
Panel E: $_q$CFP EW HIGH ESG	**.0069*****	.0013
	(.0025)	(.0026)
Panel F: $_q$CFP EW LOW ESG	.0056	
	(.0038)	
Panel G: $_q$CFP VW HIGH ESG	.0056	-.0010
	(.0035)	(.0029)
Panel H: $_q$CFP VW LOW ESG	**.0066***	
	(.0036)	
Panel I: $_q$OCFP EW HIGH ESG	**.0035***	-.0012
	(.0021)	(.0024)
Panel J: $_q$OCFP EW LOW ESG	.0047	
	(.0036)	
Panel K: $_q$OCFP VW HIGH	.0028	-.0022
	(.0032)	(.0027)
Panel L: $_q$OCFP VW LOW	.0050	
	(.0033)	

Table A.21: *Displays the average returns of the HML portfolios based on the 4-quarter change in Return on Equity (dROE) and its robustness check the pure Return on equity (ROE) anomaly. The HML column demonstrates the difference between the fifth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-D displays the return of the strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

	HML	**DIFF**
Panel A: dROE EW	**.0082*** (.0018)**	
Panel B: dROE VW	**.0106*** (.0022)**	
Panel C: ROE EW	**.0051*** (.0019)**	
Panel D: ROE VW	**.0093*** (.0023)**	
Panel E: dROE EW HIGH ESG	**.0079*** (.0022)**	**.0009 (.0029)**
Panel F: dROE EW LOW ESG	**.0070** (.0029)**	
Panel G: dROE VW HIGH ESG	**.0097*** (.0023)**	.0008 (.0032)
Panel H: dROE VW LOW ESG	**.0089*** (.0030)**	
Panel I: ROE EW HIGH ESG	**.0072*** (.0024)**	.0012 (.0026)
Panel J: ROE EW LOW ESG	**.0060*** **	
Panel K: ROE VW HIGH ESG	**.0122*** (.0031)**	.0049 (.0031)
Panel L: ROE VW LOW ESG	**.0073*** (0.0024)**	

Table A.22: *Displays the average returns of the HML portfolios based on the 4-quarter change in Return on Equity (dROE) and its robustness check the pure Return on equity (ROE) anomaly by excluding financial firms. The HML column demonstrates the difference between the fifth portfolio and the first portfolio, the significance of the HML return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the HML portfolio of high ESG stocks while going short in the HML portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-D displays the return of the strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

	HML	DIFF
Panel A: dROE EW	**0.0090*** (0.0018)**	
Panel B: dROE VW	**0.0112*** (0.0020)**	
Panel C: ROE EW	**0.0050** (0.0020)**	
Panel D: ROE VW	**0.0078*** (0.0021)**	
Panel E: dROE EW HIGH ESG	**0.0074*** (0.0024)**	-0.0005 (0.0034)
Panel F: dROE EW LOW ESG	**0.0079** (0.0032)**	
Panel G: dROE VW HIGH ESG	**0.0094*** (0.0019)**	-0.0006 (0.0039)
Panel H: dROE VW LOW ESG	**0.0100*** (0.0036)**	
Panel I: ROE EW HIGH ESG	**0.0062*** (0.0023)**	0.0042 (0.0027)
Panel J: ROE EW LOW ESG	**0.0058** (0.0023)**	
Panel K: ROE VW HIGH ESG	**0.0094*** (0.0022)**	0.0004 (0.0026)
Panel L: ROE VW LOW ESG	**0.0053** (0.0021)**	

Table A.23: *Displays the average returns of the HML portfolios based on Total Volatility (VOL) and its robustness test Idiosyncratic Volatility (IDIO-VOL). The LMH column demonstrates the difference between the first portfolio and the fifth portfolio, the significance of the LMH return, and the Newey-West standard deviation. The DIFF column represents the portfolio return of a portfolio that takes a long position in the LMH portfolio of high ESG stocks while going short in the LMH portfolio of low ESG stocks, displayed with Newey-West standard errors and the significance level. Panel A-D displays the return of the single-sorted strategy regressed on the entire sample, while Panel E-L displays the double-sorted return based on the anomaly value and ESG scores. Each strategy is presented with its Equal Weighted (EW) and Value Weighted (VW) returns. NYSE breakpoints are applied for both single and double-sorted portfolios. Significance is defined as * p <0.10, ** p <0.05, *** p <0.01.*

	HML	**DIFF**
Panel A: VOL EW	**-.0090**** (.0036)**	
Panel B: VOL VW	**-.0054 (.0038)**	
Panel C: IDIO-VOL EW	**-.0064*** (.0025)**	
Panel D: IDIO-VOL VW	**-.0036 (.0029)**	
Panel E: VOL EW HIGH ESG	**-.0042 (.0043)**	**.0043 (.0032)**
Panel F: VOL EW LOW ESG	**-.0085** (.0036)**	
Panel G: VOL VW HIGH ESG	**-.0016 (.0043)**	**.0053 (.0042)**
Panel H: VOL VW LOW ESG	**-.0069** (.0032)**	
Panel I: IDIO-VOL EW HIGH ESG	**-.0018 (.0033)**	.0053* (.0028)
Panel J: IDIO-VOL EW LOW ESG	**-.0071*** (.0027)**	
Panel K: IDIO-VOL VW HIGH ESG	**-.0021 (.0035)**	.0030 (.0034)
Panel L: IDIO-VOL VW LOW ESG	**-.0050* (.0026)**	