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Chasing Returns: Investor Attention's Impact on ESG Stocks

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ABSTRACT

This thesis examines whether investor attention, measured by Google searches, influences the effect ESG has on stock returns. This study contributes to the existing literature by analyzing the unidentified effect of investor attention on the returns of ESG stocks. Before, prior research merely examined the sole effects of ESG and investor attention on stock returns. This thesis combines both aspects by measuring the financial performance using global stock data (MSCI World Index) from 2013 to 2019. Using yearly ESG scores from ASSET4 and weekly Google Search Volume data for ticker code, company name, and composite Google searches, this study establishes an econometric framework structured from simple to more extensive analyses. First, this thesis applies a single and double sorting approach with the CAPM and the Carhart (1997) four-factor model to determine the risk-adjusted returns of the portfolios sorted in terciles and deciles. Second, due to the disparity in data frequency, more extensive analyses are needed to determine investor attention's additional effect on returns per ESG-rated portfolio. These analyses include panel regressions, a vector autoregression model, and Granger causality tests. This research reveals that corporate socially responsibility (CSR) is not crucial within investment decisions to earn higher alpha. Investing in low ESG-rated firms leads to higher alpha. Moreover, high investor attention impacts stock returns when integrating ESG factors into investment decisions, especially for medium and high ESG scores. In all, these results expand the existing literature regarding the unidentified investor attention' impact on ESG stocks' returns.

Keywords:

ESG investing, Investor Attention, Asset Pricing Models, Portfolio Performance, Vector Autoregression

JEL: G11, G12, G14, C32

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1 INTRODUCTION

“ESG investing is not just another stock bubble” (MSCI, 2021)

In recent years, Social Responsible Investment (SRI) increasingly obtained attention of both the general public and the business community. According to the US SIF (2020), investors have been adding and applying SRI criteria to their investment strategies. As a result, companies have started to experience pressure to integrate corporate social responsibility (CSR) in their future business models next to their own socially well-doing philosophy. Accordingly, this led to the implementation of Environmental, Social, and Governance (ESG) factors within their businesses. ESG investing has not gone unnoticed by investors as some state that *“ESG investing is the new gold”* whereby the Covid-19 pandemic made ESG investing even hotter. Since ESG investing’s attention increased significantly over the last few years, the effect of investor attention on ESG returns is instructive to research.

To-date studies find ambiguous relationships between financial performance and ESG performance. The returns of ESG integrated firms revealed varied insights due to different ratings, periods, and market conditions. Highly rated ESG firms showed outperformance until 2004, whereas this trend stagnated after 2004 and has been picking up shortly. Future expectations express the importance of ESG integration to make a long-term impact from a sustainable and financial perspective.
Hence, businesses accelerate efforts to integrate ESG. Besides that, investors are also full steam ahead on ESG. Given the hot topic of ESG investing, the causal relation between ESG investing and investor attention is relatively unknown in the academic field. The sole effects of ESG-rated firms and investor attention on stock returns are widely studied within the financial academic field. However, the relation of ESG and investor attention and its combined effect on stock performance is unclear in current literature. Available research shows that greater investor attention leads to price pressure and the increasing speed of information processing into stock prices, increasing market efficiency. However, the association of investor attention with ESG scores is unidentified.

With that in mind, the underlying thesis focuses on shedding light on the financial effect of ESG and investor attention on stock returns. The reasoning behind this research is to examine the unidentified combined effect of both ESG and investor attention expressed in financial performance. For this purpose, this thesis proposes the following research question:

“Does high investor attention influence the effect ESG has on stock returns?”

The main objective of the above research question is to examine whether investor attention, due to a higher demand for ESG stocks, could positively affect the stock performance of ESG firms. This thesis imitates the MSCI World Index to obtain a dataset with firms that have global coverage across developed markets over the period 2013 - 2019. To obtain ESG and investor attention data, this research uses the databases ASSET4 Thomson Reuters and Google Trends, respectively. Google Trends shows how often a specific search term is entered relative to the total Google search query volume.

This thesis uses several research approaches to test the above research question. Firstly, asset pricing models examine the separate effects of ESG and investor attention within a single sorting approach. Subsequently, a double sorting approach investigates the combined effect on performance. The downfall of the single and double sorting methods is that much explanatory information is lost due to the portfolio's mean values. Therefore, this thesis performs additional analyses to find the individual effects of investor attention on performance for three ESG-rated portfolios. These analyses include lagged panel regressions, a vector autoregression model, and Granger causality tests. The intention behind these additional tests is to examine how investor attention affects performance per ESG-rated portfolio.

This paper finds that the additional effect of investor attention deviates per ESG-rated portfolio, showing the most robust results for medium and high ESG-rated portfolios, which is different from prior research. This paper's findings interpret that corporate social responsibility (CSR) is not crucial within investment decisions to earn higher alpha. In fact, investing in low ESG-rated stocks lead to higher alpha which is in line with Pastor et al. (2020). However, investors are getting serious about climate change, therefore holding ESG stocks (MSCI, 2021). Moreover, firms with high attention have more effect on returns when integrating ESG factors into investment decisions.

The remainder of this research is structured as follows: Chapter 2, the literature review, dives deeper into the existing literature by briefly describing the separate and combined effects of ESG and investor attention on stock performance. Chapter 3 explains the data collection of ESG and investor attention. Chapter 4 elaborates on the methodology used in this research. Chapter 5 analyses the results for all the hypotheses stated in section 2.4. Chapter 6 reflects on the obtained results and identified limitations in the discussion section. Finally, Chapter 7 provides a clear overview of conclusions on the obtained results.

2 LITERATURE REVIEW

Underlying literature review will shed light on the different components of this thesis. Firstly, the relation between ESG scores and stock performance will be researched. Moreover, the second section reveals the effect of investor attention on stock performance. Lastly, the third section focuses on the combined effect of ESG scores and investor attention on stock performance. These three components will introduce the stated hypotheses in the fourth section of this literature review.

2.1 ESG and stock performance

The first section of this literature review focuses on the effect of ESG scores on the performance of stocks. The main focus is to evaluate the effects that have been found in previous studies. In line with the ESG studies overview in Table 1, the beneath most important findings explain the trends of ESG investing.

Firstly, Kempf and Osthoff (2007) find significantly positive four-factor alphas of 5% per year using a 10% deduction of industry-adjusted ESG scores in their research. They construct long-short value-weighted portfolios, including stocks from the S&P 500 and the Domini 400 Social Index (DS 400) during 1992 – 2004. Investors can earn abnormal higher returns by following this long-short strategy by implementing a positive screening approach. However, this does not hold for the negative screening approach. The best-in-class approach shows the highest alphas, which are up to 8.7% per year (Kempf & Osthoff, 2007).

Moreover, Statman and Glushkov (2009) support the findings of Kempf and Osthoff (2007) by analyzing the returns of stocks rated on social responsibility factors by KLD during the period 1992 – 2007. They find that tilt allowed socially responsible portfolios to outperform ordinary portfolios by excluding shunned firms' stocks (Statman & Glushkov, 2009). Both papers also show that portfolios formed on community and employee relations reveal the highest returns, while environment, products, human rights, and diversity have no significant effect on returns (Kempf & Osthoff, 2007; Statman & Glushkov, 2009). However, Climent and Soriano (2011) find that US green mutual funds do not outperform their conventional peers using a CAPM-based model from 1987 – 2009.

Borgers et al. (2013) build further on the research of Kempf and Osthoff (2007) and show that ESG outperformance vanishes over the years during the period 1992 – 2009. They use different ESG cut-off points to build a long-short equal- and value-weighted portfolio. All four-factor alphas are significant and positive until the year 2004. From 2004, the alphas are insignificant and close to zero. These results are robust to changes in the ESG estimate, including industry adjustments (Borgers et al., 2013).

Mollet and Ziegler (2014) find a negative relationship between SRI and stock performance from 1998 to 2009 by using the ASSET4 database for ESG scores. The results of the Carhart (1997) four-factor model reveals insignificant abnormal returns exist for large firms with SRI in the US and European stock market.

In line with Borgers et al. (2013), Halbritter and Dorfleitner (2015) also show early outperformance followed by insignificant returns over the same period of 2001 to 2012. Moreover, their sample compared data of ASSET4 and Bloomberg next to the data of KLD to measure the returns of ESG-rated firms (Halbritter & Dorfleitner, 2015). Both ASSET4 and Bloomberg show insignificant alphas for the more recent periods 2003 – 2012 (ASSET4) and 2006 – 2012 (Bloomberg). These results are in line with the KLD results for the later period. However, when they perform Fama and MacBeth's (1973) cross-sectional regression, the returns due to ESG scores of ASSET4 and Bloomberg become highly positive and significant while KLD stays insignificant. This difference observed is unusual unless both regressions use different weightings and factor loadings within the portfolios. The paper of Halbritter and Dorfleitner (2015) indicates that different ESG data sources like KLD, ASSET4, Bloomberg, and Sustainalytics lead to different outcomes. Therefore, the results of Halbritter and Dorfleitner (2015) should be checked for robustness.

Nagy et al. (2016) research if incorporating ESG leads to higher risk-adjusted returns. They find that both the "ESG tilt" and "ESG momentum" strategies have outperformed the global benchmark MSCI World Index using MSCI's ESG data over the period 2007 – 2015 while systematically improving the ESG profile of their portfolios. The ESG tilt strategy links ESG scores to long-term future stock performance. They consider that companies that integrate ESG considerations into their operations can exploit ESG-related opportunities like clean technologies and prevent some financial losses related to ESG. Nagy et al. (2016) conclude that tilting toward higher ESG score positively affects the overall ESG profiles of portfolios. Moreover, next to tilting the portfolio toward a higher ESG rated companies, the ESG momentum strategy aims to give more explanatory power to firms that increased their rating during the past 12 months. They find that this more short-term strategy links future stock performance to the company's change in ESG quality. For both strategies, a significant portion of outperformance sources was due to stock-specific sources, which could indirectly be linked to ESG signals (Nagy et al., 2016).

Ashwin Kumar et al. (2016) construct 12 equally weighted portfolios that group stocks based on industries. In their two-year sample period (2014 – 2015), they found three significant results. Firstly, ESG firms have lower volatility in their stock returns than their reference firms in the same industry. Secondly, ESG factors impact each industry differently. Lastly, ESG firms within the Dow Jones

Sustainability Index have higher risk-adjusted returns of 6.12% on average than their peers measured by the Sharpe ratio and Treynor ratio (Ashwin Kumar et al., 2016).

Many of the above research confirms that stocks with a high ESG score have higher excess returns. However, not all studies show a positive relationship between ESG and stock returns. A recent study by Lööf and Stephan (2019) finds no systematic relationship between ESG and risk-adjusted returns for European countries over the period 2005 to 2017. However, ESG scores do decrease the downside risk of stock returns. Moreover, Torre et al. (2020) find that higher ESG scores overall do not significantly affect the returns of companies included in the Eurostoxx50 index over the period 2010 – 2018. However, they find that the ESG score for a few firms, mostly working in particular sectors like energy and utilities, positively impacts their stock returns (Torre et al., 2020). In line with Lööf and Stephan (2019), new insights by Drei et al. (2019) show that ESG investing did not result in higher alpha between 2010 and 2013. Nonetheless, after that period, ESG investing revealed outperformance in North America and Europe from 2014 to 2019.

The most recent paper by Pastor et al. (2020) explains the construction of an ESG factor. They find that ESG preferences change asset prices. Stocks of more sustainable firms have lower expected returns, especially when ESG preference is strong and risk aversion is low. Pastor et al. (2020) observe that green (sustainable) stocks have negative alphas, and that brown (unsustainable) stocks have positive alphas. Nevertheless, the negative alphas for greens stocks, investors' main reason for holding those stocks is investors' ESG taste. Pastor et al. (2020) introduce a green-minus-brown portfolio that uses the ESG factor to determine returns between both assets. Their research's main implication is that despite the lower alphas of green stocks, investors prefer to hold more sustainable stocks for climate reasons and positive social impact.

Finally, a comprehensive study by Clark et al. (2015) reviewed 41 previous papers on sustainability and its effect on financial market performance. They found that 80% of these studies (33) showed a positive relationship between high ESG and financial market performance. These findings suggest that investing in firms with a high ESG score leads to earning positive alpha. According to the above papers, superior sustainability quality, measured in aggregate sustainability scores (ESG), is valued positively in the stock market. This means that more sustainable firms generally outperform less sustainable firms (Clark et al., 2015).

In brief, the above papers show that highly rated ESG firms experienced stock outperformance relative to low ESG firms in the period from 1992 to 2004. However, most research showed reverse findings after 2004 as the alphas for high ESG firms became insignificant. Nevertheless, as the results of Clark et al. (2015) suggest, ESG leads to earning higher alpha when investing in ESG firms. Moreover, Pastor et al. (2020) point out that investors hold green stocks, despite the negative alphas, due to strong ESG preferences. This strong ESG preference is expected to grow in the coming years due to heavy climate change realization.

Table 1: Overview of ESG studies

Author(s) (publication year)	**Time**	**Model**	**ESG and stock data**	**Results**
Kempf and Osthoff (2007)	1992 - 2004	Long-short portfolios with 4-factor model	KLD CRSP stock database	Up to 8.7% alpha per year
Statman and Glushkov (2009)	1992 – 2007	Asset pricing models (CAPM, 3- & 4- factor models)	KLD Domini 400 Social Index (DS 400) S&P 500	SRI portfolios outperform ordinary portfolios
Climent and Soriano (2011)	1987 – 2009	Asset pricing models (4-factor model)	CRSP Bloomberg KLD400	US green funds do not outperform (2001 – 2009)
Borgers et al. (2013)	1992 - 2009	Asset pricing models (4-factor model)	KLD S&P 500	ESG outperforms until 2004
Mollet and Ziegler (2014)	1998 – 2009	Carhart four-factor model	ZKB Thomson Reuters Datastream	Insignificant abnormal stock returns for SRI
Halbritter and Dorfleitner (2015)	1991 - 2012	Carhart 4-factor model and Fama and Macbeth cross-sectional regression	ASSET4, Bloomberg and KLD US stocks	ESG outperformance (1991 – 2002) Insignificant alphas (2003 – 2012) Highly significant alphas for Fama and Macbeth (ASSET4 and Bloomberg)
Nagy et al. (2016)	2007 – 2015	Portfolio evaluation	MSCI World Index	Both ESG tilt and momentum strategies outperformed

Ashwin Kumar et al. (2016)	2014 – 2015	Performance evaluation Sharpe ratio	ESG Dow Jones Sustainability Index	ESG firms on DJSI have higher returns
Lööf and Stephan (2019)	2005 – 2017	Fama and French 3-factor model	Sustainalytics Thomson Reuters Datastream	No systematic relationship between ESG and risk-adjusted returns
Drei et al. (2019)	2010 – 2019	Factor analysis Long-short portfolios	MSCI North America and MSCI EMU indices	No significant outperformance (2010 to 2013) Major ESG outperformance (2014 to 2019)
Torre et al. (2020)	2010 – 2018	Multiple linear regression	CSRHub Eurostoxx50	ESG does not outperform
Pastor et al. (2020)	Comparing several time periods from earlier papers	CAPM ESG factor portfolios	Comparing several databases from earlier papers	Green stocks have negative alphas (investors hold because of ESG taste) Brown stocks have positive alphas

2.2 Investor attention and stock performance

The second section of this literature review studies the effect of investor attention on stock performance. The main focus is to explain the distinction between media and investor attention and subsequently study the effects on returns that have been found in previous studies. Beneath findings explain the relation between investor attention and stock returns in line with the investor attention studies overview in Table 2.

Merton (1987) shows that the pricing of stocks is diversified imperfectly because investors only have limited attention. Low attention firms should offer higher returns to compensate for the imperfect diversification. Therefore, at the same time, more attention for stocks should result in a price increase followed by lower future returns in the long run. A highly cited paper by Fang and Peress (2009) finds that stocks without media attention earn higher returns than stocks with high media coverage. However, they make no difference between good or bad news in their cross-sectional research. This finding is in line with the findings of Merton (1987). As explained by Fang and Peress (2009), there should be made a difference between "news" and "coverage". Fang and Peress (2009) use the database LexisNexis as database for the collection of the number of newspaper articles about a stock to proxy for the stock's overall media exposure. LexisNexis is a widely used database for the collection of news articles.

Weaver and Bimber (2008) compare Google News's databases to LexisNexis for finding stories in big newspapers. They find that LexisNexis missed half or more articles appearing in major newspapers. This indicates the precision of media coverage gathered by Google News. Moreover, the number of newspaper articles is not reliable enough as measure to the extent a reader pays attention to a specific firm in the newspaper. Hence, Bank et al. (2011) and Da et al. (2011) use Google search volume of company names to proxy investor attention. They state that number of searches for a particular company or stock is a good indicator of public interest. This is mainly due to the rise of the Internet over the past years and the underlying interest when a user specifically searches for a stock or a company.

In line with the above findings, this thesis's scope is on a relatively new researched phenomenon within the media coverage field, namely investor attention measured by Google searches. Investor attention evaluates the amount of Google searches a particular company or stock has relative to other companies. This will be assessed through the search engine Google Trends Search Volume Index. The Google search volume (GSV) shows a relative value which gives investor attention a more explanatory value (Da et al., 2011).

Barber and Odean (2008) explain that individual investors tend to buy stocks that have been in the news and have high abnormal trading volumes and extreme short-term returns of a day, also known as the attention-grabbing hypothesis. Da et al. (2011) support the research of Barber and Odean (2008) and observe that stocks emerging on Google searches are short-term inflated followed by lower returns. The same reasoning says that stocks are underpriced at less attention leading to higher future returns (Da et al., 2011).

In line with Barber and Odean (2008) and Da et al. (2011), Bank et al. (2011) research how Google search volume influences liquidity and returns of German stocks. They find that a higher search volume of company names on Google results in rising future returns in the short-term, which disappears in the long run. Bank et al. (2011) state that this effect is mainly due to the price pressure caused by individual investors. To measure the effect between Google search volume and stock returns, Bank et al. (2011) use the same multivariate analysis as Fang and Peress (2009) that controls for risk factors to calculate returns. Their research sorts the stocks monthly into three equal-sized quantiles according to varying Google search volumes. Subsequently, they perform a zero-investment strategy. Hereby going long in the portfolio with the highest realized search volume change and short in the portfolio with the lowest realized search volume. Bank et al. (2011) use three different factor models to assess whether the monthly portfolios' equally-weighted average returns are different from zero. These models are the market model (CAPM), the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model.

Joseph et al. (2011) show that the intensity of online search queries of an S&P500 firm's ticker code accurately forecasts abnormal stock returns and trading volumes. These findings are the strongest for easy-to-arbitrage and low volatility stocks (Joseph et al., 2011). Regarding volatility stocks, Blitz et al. (2014) and Beveratos et al. (2017) explain that stocks with low volatility are considered boring and therefore call for a premium in relation to high attention so-called glittering stocks.

In line with Joseph et al. (2011), Vlastakis and Markellos (2012) reveal that Internet search volume is positively correlated with trading volume and return volatility for 30 stocks trading on NYSE by using of Google Trends as investor attention measurement. They also find that attention increases significantly during periods of higher returns. Conversely, Antweiler and Frank (2004) find that news predicts market volatility but that the effect on returns is small.

Moreover, Zhang et al. (2013) use the Chinese equivalent of Google Trends named Baidu index as proxy investor attention by company name searches. They find that investor attention is the desired variable to predict abnormal stock return. Moreover, they find a strong contemporary relationship between investor attention and abnormal return. Furthermore, they performed Granger causality tests that revealed a bi-directional pattern that can be mainly explained by overconfidence, which is the psychological bias of investors. Lastly, they found that the impact investor attention variations reveal that searching for company information enhances the speed of information from the public to a wider range of investors and, therefore, into stock prices. This last effect results in increasing market efficiency due to more information.

In line with Zhang et al. (2013), Vozlyublennaia (2014) examines the causal effect of Google searches on stock index returns. The paper finds that attention influences indexes for stocks in the short run. Moreover, returns significantly affect attention in the long run. Lastly, past returns predict attention which impacts current returns. In short, his findings conclude that investor attention decreases return predictability and therefore enhances market efficiency.

Subsequently, Chen (2017) finds that investor attention has a significant and negative influence on stock returns. He uses weekly data Google ticker search data and converts it into a monthly format in his study. He finds that the negative effect of investor attention is strengthened or weakened based on market sentiments. The return predictability of his model holds for six months and may be attributable to local attention. These findings are in line with the investor recognition hypothesis of Merton (1987) and Fang and Peress (2009).

Blitz et al. (2020) test whether this attention-grabbing hypothesis of global stocks explains the volatility effect in the period 2001 – 2018. They find that media attention and volatility are positively correlated, indicating that the low-volatility effect is explained by media attention. Moreover, they use a double-sorting approach to find the driving force behind the volatility effect. Hereby Blitz et al. (2020) calculate the equally weight monthly-stock returns by sorting 25 portfolios on every combination of volatility and media attention. Their research’s most vital result is that media attention has no standalone effect in the global equity market. Moreover, they find that low-volatility portfolios have higher risk-adjusted returns than high-volatility portfolios due to their positive alpha for high attention stocks. Furthermore, the level of media attention has no significant effect on high volatility stocks. Therefore, Blitz et al. (2020) conclude that the attention-grabbing hypothesis does not explain their sample’s volatility effect.

In short, above studies reveal that Google search queries are a reliable measurement of investment attention. Moreover, the attention-grabbing hypothesis shows that stocks are short-term inflated followed by lower returns due to Google searches. To conclude, this indicates that low investor attention stocks have higher returns than high investor attention stocks.

Table 2: Overview of investor attention studies

Author(s) (publication year)	**Time**	**Model**	**Attention and stock data**	**Results**
Weaver and Bimber (2008)	2006 - 2007	Comparing databases for attention accuracy	Google News LexisNexis	Google News captures more accurately attention over newspapers
Barber and Odean (2008)	1991 - 1996	Abnormal trading volume and extreme returns evaluation	Plexus Group CRSP (US stocks)	Attention-grabbing hypothesis
Fang and Peress (2009)	1993 – 2002	Uni- and multivariate analysis	US news papers (LexisNexis) NASDAQ	Stocks without media attention earn higher returns
Bank et al. (2011)	2004 – 2010	Univariate analysis: Single and double sorted portfolios Multivariate analysis: Panel estimations	Google searches German stocks (Thomson Reuters Datastream)	Increase in attention leads to temporarily higher returns Market efficiency
Da et al. (2011)	2004 – 2008	Abnormal Google searches & Vector autoregression (VAR) model	Google Search Volume Index Russell 3000 stocks	Increase in investor attention predicts higher stock prices in 2 weeks and an eventual price reversal within a year
Joseph et al. (2011)	2005 – 2008	Asset pricing models (Carhart 4-factor model)	Google Insights S&P500 (CRSP)	Ticker searches predict abnormal stock returns and trading volume
Vlastakis and Markellos (2012)	2004 – 2009	Granger causality tests, Correlation analysis	Google ticker searches NYSE and NASDAQ	Attention positively correlated with trading volume and return volatility

Zhang et al. (2013)	2011 - 2012	Correlation analysis Granger causality tests	Baidu index China Stock Market	Strong relationship between investor attention and abnormal returns
Vozlyublennaia (2014)	2004 - 2012	Granger causality tests and VAR	Google Trends Dow, S&P 500 and NASDAQ (stocks)	Increased attention results in more market efficiency
Chen (2017)	2004 – 2014	Long term analysis: VAR Market sentiment analysis	Google Trends Global stock markets (Bloomberg)	Attention has a negative influence on stock returns
Blitz et al. (2020)	2001 – 2018	Single and double sorting approach	Ravenpack MSCI World Index S&P500	Media attention not driving force behind the volatility effect

2.3 ESG & Investor attention and its effect on stock performance

The third section of the literature review evaluates the combined effect of ESG and investor attention on stock performance. This section's main focus is to study previously found results to set up preliminary research methods.

The vast majority of attention literature within the financial field is devoted to stock returns. This thesis contributes to earlier research on CSR awareness's importance (McWilliams and Siegel, 2001; Schuler and Cording, 2006; and Servaes and Tamayo, 2013) and links this to stock performance. Former empirical research measured attention through the number of news articles a particular company or stock had. By measuring this, researchers could distinguish attention from no attention and good news from bad news within the media coverage.

Firstly, Zyglidopoulos et al. (2012) find that attention could be considered an essential stimulus for behaving better in terms of corporate social responsibility. In line with Zyglidopoulos et al. (2012), Cahan et al. (2015) research if companies with more corporate social responsibility (CSR) gain more positive attention and if CSR is used to guide their media image. Firstly, Cahan et al. (2015) find that firms with high CSR investments receive more favorable news coverage and build an overall positive media image. Secondly, the relation between favorable media coverage and CSR is stronger when a firm has the incentive to enhance its media image. This active media management is mostly seen at companies within sin industries (unethical industries such as alcohol, tobacco, and gambling). They have bigger incentives to earn more goodwill by having more CSR media coverage. This concept is widely known as greenwashing. Thirdly, Cahan et al. (2015) find that CSR and media attention's incremental economic effect is economically significant for both a higher Tobin's Q and a decreasing cost of capital when both coefficients have a high news favorability and a high CSR performance. Therefore, companies with a high CSR performance capitalize better firm value and have a lower cost of capital due to favorable attention (Cahan et al., 2015). Besides the favorable effect of CSR on attention, the direct effect on stock performance is not elaborated in the latter two papers.

Additional research by Cheung (2011) does reveal an effect of ESG attention on stock prices. They find that the addition to the Dow Jones Sustainability World index has a temporarily positive effect on respective stock prices and exclusion of the index has a negative effect. Moreover, research shows that exclusion from sustainability stock indices results in significant negative stock price reactions (Brammer & Millington, 2008; Doh et al., 2010). Furthermore, Cheung (2011) find a similar result that there is no significant effect on stock return of stocks that are in- or excluded from the Dow Jones Sustainability World Index over the period 2002 – 2008. Their event study reveals only a temporary increase or decrease on the day of index inclusion or exclusion is significant but holds for that day (Cheung, 2011). These findings indicate that ESG leads to more investor attention and therefore, temporarily affects stock prices.

Moreover, Krüger (2015) examines the stock market reaction to positive and negative CSR appearances in the news. Firstly, he performs an event study to determine how positive and negative news of different ESG factors impacts the cumulative abnormal returns. He finds that negative events have a significant negative impact on stock prices and that positive events have a less systematic impact on stock prices depending on the quality relations between the businesses and their stakeholders (Krüger, 2015). However, prior research by Flammer (2013) does find a significant effect of ESG news on the stock market for companies with a higher environmental CSR both on the respective eco-friendly and harmful side.

Accordingly, Byun and Oh (2018) measure CSR media coverage's value and its impact on firm value. They find that shareholders are most significantly positive towards CSR media covered in local-oriented ESG activities. Li et al. (2017) find that ESG performance is positively associated with firm value. Moreover, they show that media attention has a mediating effect between ESG and firm value. However, note that this study is performed only for Chinese manufacturing firms, which may lack social and environmental regulations (Li et al., 2017).

Additional research by Capelle-Blancard and Petit (2019) also perform an event study on the positive and negative news related to ESG factors and their effect on the stock market. They find similar results in line with Krüger (2015) as firm's market value declined by 0.1% due to negative events within a 3-

day window and have no significant effect on positive ESG news. Their sample contains 33,000 ESG news events, extreme and ordinary events, from 2002 to 2010 (Capelle-Blancard & Petit, 2019). Another event study by Du et al. (2017) focuses on sustainability reporting as a sustainability communication measure. They find that releasing ESG reports significantly influences the stock market temporarily. The abnormal stock returns are positively correlated to the ESG score of a firm. This correlation is lower for firms that actively report their ESG reports. Moreover, Du et al. (2017) highlight that ESG reporting firms have more impact on stock performance in the long run than non-reporting ESG firms.

Moreover, recent research by Ender and Brinckmann (2019) also performs an event study to measure ESG news's impact on stock prices. They find that both positive and negative ESG-related news significantly had an overall positive effect on accumulated short-term abnormal returns in an event-window of 5 days. Moreover, recent research by Guo (2020) shows that ESG related financial news has a significant effect on future risk-adjusted returns.

Lastly, Sabbaghi (2020) shows that by performing an EGARCH framework, the impact of news on the volatility of ESG companies is bigger for bad news than for good news. The increase in volatility is lower for small size ESG companies than large- and mid-cap ESG companies. Moreover, small size ESG companies are less sensitive to the size of market movements. Therefore, small size companies react slower to ESG related news (Sabbaghi, 2020). Thus, size and attention are positively related. Large size firms have more investor attention. Based on this finding, it might be important to control for firm size in this research.

In short, above prior literature reveal no specific effect of investor attention on ESG investing. This is an important aspect for the identification of this research. Prior research performs mostly event studies to find the effect of attention on ESG performance. New research should be conducted as the to-date literature did not shed light on the combination of investor attention and ESG investing on stock returns. Therefore, the effect of investor attention on the financial performance of ESG-rated stocks will be the specific research design of this paper. Firstly, this paper follows Blitz et al. (2020) by using their single and double sorting approaches as preliminary research design. Moreover, additional analyses are required to examine the closer effects of investor attention on different ESG-rated portfolios' performance.

2.4 Hypotheses

Above literature review of this thesis sheds light on the separate and combined effects of ESG ratings and investor attention on stock returns. Beneath section sums up the main takeaways to correctly state the main research question of this thesis. Firstly, the outperformance of high ESG-rated stocks shows mixed results over the existence of ESG ratings. However, overall high ESG-rated firms outperform and are expected to outperform in the future due to the increasing importance of CSR. Moreover, recent research reveals the important finding that investors will hold on to green stocks regardless of the alpha earned due to strong ESG preference (Pastor et al., 2020). The second section of the literature review reveals that high attention stocks do not necessarily outperform but only show temporarily abnormal returns. In line with the attention-grabbing hypothesis, a moderating effect of investor attention is expected. Based on the above findings, the following main research question is therefore as follows:

"Does high investor attention influence the effect ESG has on stock returns?"

This thesis divides its research into different stages structured from simple to more extensive analysis to answer the above research question. Hence, the six hypotheses below are stated to test for the univariate and multivariate analysis conducted in this research. The first objective is to find the standalone effect of ESG performance measured by its ESG score on stock returns. Therefore, coherent with the literature stated above, this thesis addresses the first hypothesis:

***Hypothesis 1**: "High-rated ESG firms have higher risk-adjusted returns than low-rated ESG firms."*

Further aim of this thesis is to determine the effect of investor attention on stock returns in the single sorting approach. Hence, the second hypothesis is proposed:

***H2**: "Firms with low investor attention have higher risk-adjusted returns than high investor attention firms."*

As investor attention is measured by Google searches for its ticker code, and company name, the separate effects and composite effect of both will be evaluated for all three attention measures. Thus, the second stage will be divided into the following hypotheses:

> ***Hypothesis 2a**: "Firms with low investor attention by ticker searches have higher risk-adjusted returns than high investor attention firms."*
>
> ***Hypothesis 2b**: "Firms with low investor attention by company name searches have higher risk-adjusted returns than high investor attention firms."*
>
> ***Hypothesis 2c**: "Firms with low investor attention by composite searches have higher risk-adjusted returns than high investor attention firms."*

Subsequently, after examining the separate effects for both ESG and investor attention, the combined effects are researched in the double sorting approach.

H3*: "High-rated ESG firms and firms with low investor attention have the highest risk-adjusted returns relative to the other combinations."*

Again, the double sorting hypothesis examines investor attention per attention measure. Therefore, the third hypothesis divides the following sub-hypotheses in ticker, company name, and composite searches:

> ***Hypothesis 3a****: "High-rated ESG firms and firms with low investor attention by ticker searches have the highest risk-adjusted returns relative to the other combinations."*
>
> ***Hypothesis 3b****: "High-rated ESG firms and firms with low investor attention by company name searches have the highest risk-adjusted returns relative to the other combinations."*
>
> ***Hypothesis 3c****: "High-rated ESG firms and firms with low investor attention by composite searches have the highest risk-adjusted returns relative to the other combinations."*

More extensive analyses are needed to measure investor attention's additional effect beyond the ESG rating of firms. Therefore, this research performs multivariate analyses in the last stages of this paper. Firstly, lagged panel regressions examine the individual effects of investor attention for each firm. Hence, the fourth hypotheses are:

Hypothesis 4a*: "Investor attention has a significant effect on returns in high-rated ESG portfolios."*

Hypothesis 4b*: "Returns has a significant effect on investor attention in high-rated ESG portfolios."*

Furthermore, this paper performs a vector autoregression (VAR) model with the accordingly Granger causality tests. The exact use of the Granger causality tests within this research is explained in section 4.2. The fifth hypotheses are the following:

Hypothesis 5a*: "Investor attention Granger causes returns in high-rated ESG portfolios."*

Hypothesis 5b*: "Returns Granger cause investor attention in high-rated ESG portfolios."*

3 DATA

3.1 Data collection

This section sheds light on the sources of data and briefly explains the data collection. The first part of the data collection section explains the gathering of the ESG factors. The second part shows the data collection of Google Trends for the measure of investor attention. Lastly, the last part of this section shows the descriptive statistics for both measures, including the control variables.

3.1.1 ESG

For this research, the performance of listed firms will be obtained for the period 2013 to 2019. This specific time period is chosen to give an accurate overview of recent stock performance by disregarding the Financial crisis of 2007-2008. Smoothing out this period and the few years thereafter will not give distorted results regarding the crisis. In line with Blitz et al. (2020), the MSCI World Index will be used as a reference to obtain a dataset of listed firms with global coverage. The MSCI World Index consists of 1.603 worldwide stocks within developed countries weighted on market cap. The database Thomson Reuters Eikon is used in this research to mimic the MSCI World Index. Here the data sample is collected by taking all global firms with the highest market value from 2013 to 2019, resulting in an interim data sample of 9.786 firms.

Subsequently, the ESG scores of firms within the data sample are collected. In line with earlier literature, focus of this research is on ESG data provided by ASSET4 (Mollet & Ziegler, 2014; Auer & Schuhmacher, 2016; Halbritter & Dorfleitner, 2015). The Thomson Reuters ASSET4 database collects over 450 ESG indicators for all different categories of the three pillars Environmental, Social, and Governance. The environmental pillar covers the categories emission, innovation, and resource use. The social pillar accounts for community, human rights, product responsibility, and workforce. The third pillar, governance, includes the categories CSR strategy, management, and shareholders. After evaluating each pillar separately, an individual score is calculated per ESG factor. These individual pillars' scores range from 0 to 100 and are weighted based on their specific categories, indicating a relative score. Moreover, ASSET4 provides an overall ESG score based on an equal-weighted combination of all ESG pillar scores (Refinitiv, 2020). Focus will be on the latter in this research. Therefore, only the firms with an overall yearly ESG score, provided by the Thomson Reuters ASSET4 database, are gathered for the same time period (2013 – 2019). This results in a sample of 1317 global listed firms with an overall ESG score within 23 countries. Therefore, the data sample is more or less in line with the 1603 stock companies and 23 countries of the MSCI World Index.

Table 3 shows the descriptive statistics for the yearly ESG scores. The mean values range from 51.31 to 63.53 for the overall ESG scores. From the data, it can be observed that the mean value of ESG scores is increasing every year. This indicates that firms are receiving higher ESG scores on average each year which is in line with earlier research.

Table 3: ESG descriptive statistics by year

Table 3 provides the descriptive statistics for ESG per year. The table shows the mean and standard deviation values for 1,315 companies from 2013 to 2019, where N is the number of observations.

Table 3 – ESG descriptive statistics by year

	ESG	
	Mean	SD
2013	51.308	21.511
2014	52.384	20.878
2015	55.151	20.129
2016	57.733	19.141
2017	59.512	18.545
2018	61.243	18.322
2019	63.532	17.903
All	57.266	19.974
N	9,205	
Firms	1,315	

Yearly stock data and related control variables are gathered from Thomson Reuters Datastream for the global stock data sample. The descriptive statistics of these variables can be found below in Table 4A and Table 4B.

Table 4A – Stock related and control variables descriptive statistics by year

Table 4A provides the descriptive statistics for the control variables per year. The table shows the mean and standard deviation values for the returns, standard deviation, market cap (in millions), and total assets (in millions). The descriptive statistics range from 2013 to 2019, where N is the number of observations and firms the number of firms.

Table 4A - Stock related and control variables descriptive statistics by year

	Return		SD		Market Cap (mln)		Total Assets (mln)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2013	0.005	0.038	0.014	0.009	1,941,962	17,565,115	4,466.66	36,556.88
2014	0.003	0.039	0.013	0.011	2,076,247	18,798,237	5,038.64	42,387.24
2015	0.001	0.043	0.016	0.010	2,226,331	20,179,052	5,432.62	45,505.94
2016	0.002	0.041	0.015	0.011	2,320,787	22,159,037	5,926.21	51,049.83
2017	0.004	0.030	0.011	0.008	2,793,170	26,913,594	6,410.98	55,992.52
2018	-0.002	0.039	0.014	0.009	3,001,974	28,787,174	6,927.85	61,556.39
2019	0.005	0.036	0.013	0.009	3,120,693	32,007,929	7,569.24	67,749.14
All	0.003	0.038	0.014	0.010	2,501,327	24,369,134	5,965.99	52,517.92
N	475,722		477,034		477,632		9,195	
Firms	1,317		1,317		1,315		1,315	

Table 4B – Stock related and control variables descriptive statistics by year

Table 4B provides the descriptive statistics for the control variables per year. The table shows the mean and standard deviation values for Tobin’s Q, turnover, and leverage. The descriptive statistics range from 2013 to 2019, where N is the number of observations and firms the number of firms.

Table 4B - Stock related and control variables descriptive statistics by year

	Tobin's Q		Turnover		Leverage	
	Mean	SD	Mean	SD	Mean	SD
2013	1.259	1.433	35,842	113,168	0.390	0.310
2014	1.366	1.721	39,026	183,741	0.460	2.175
2015	1.456	1.963	60,043	329,912	0.428	0.539
2016	1.353	1.674	34,845	98,13	0.420	0.278
2017	1.429	1.641	33,146	96,924	0.414	0.278
2018	1.513	1.806	36,389	119,937	0.419	0.309
2019	1.461	1.795	34,186	103,971	0.431	0.306
All	1.406	1.728	38,902	168,757	0.422	0.870
N	475,563		480,705		9,505	
Firms	1,315		1,317		1,317	

3.1.2 Investor attention (Google Search Volume)

Next to the ESG data, the data collection of investor attention has a totally different approach. This section elaborates on what is the best measure for investor attention and how its data is gathered.

The mentioning of a company name or stock in a news article is a common measure of investor attention. However, a news article on a specific company does not guarantee actual attention until investors really read the article. Therefore, this research uses the abnormal search volume on Google as a more direct measure of investor attention to find the relation between investor attention and stock performance.

In recent years, a search engine is most commonly used to collect information on the Internet. Hereby Google is the most popular search engine with 92,16% of global total search queries in 2019 (StatCounter Global Stats, 2020). Moreover, the search frequency for a particular company or stock on Google reveals the direct and unambiguous interest in investing (Da et al., 2011). Da et al. (2011) use ticker codes to measure the search volume of a stock. On the contrary, Bank et al. (2011) only use company names to assess the extent of investor attention as it is unusual that Internet users search for ISIN numbers, WKN codes, or technical stock symbols. However, Joseph et al. (2011) explain that searching for a financial ticker code is the only valid proxy for investor behavior, which is in line with Da et al. (2011). They state that an investment decision is only considered serious when a potential investor takes the effort to search for a stock’s ticker code. A ticker code gives direct information about a firm's stock performance, while only searching a company's name will also give irrelevant search results (Joseph et al., 2011).

This thesis collects the weekly Google Search Volume (GSV) data from Google Trends for the same data sample of companies from 2013 to 2019. Google Trends shows how often a specific search term is entered relative to the total Google search query volume. More specifically, GSV is an index of the total search volume for a specific company name or ticker over time for global and specific region searches in this paper. This thesis collects the GSV data of both ticker symbols and company names of all 1317 firms in the data sample using a Python API web scraping interface with Google Trends. Not all stocks in our sample give enough data for the time period 2013 to 2019 due to insufficient searches or weekly data. For the ticker symbol, 1,281 search queries are left, resulting in 466,284 valid weekly observations. For company names, these are 1,258 resulting in 457,912 valid weekly observations. Therefore, the data sample drops 36 firms for ticker symbol searches and 59 firms for company name searches.

Prior papers elaborate on their attention identification choice on Google for a stock. Da et al. (2011) explain that a search engine user can search for a stock using either its ticker code or company name. The problem with searching for a company name is that investors might not search the company name for investment purposes. Moreover, the company name could have a multiple meaning as "Amazon, "Apple", or "Orange". Lastly, investors might search for the same firm using different spelling variations of its name (Da et al., 2011).

On the other hand, searching for the ticker symbol of a particular stock is less ambiguous. Investors will search for a ticker symbol when interested in the financial information about that stock. Therefore, searching for a unique ticker symbol captures the direct impact of investor attention. However, Swamy et al. (2019) explain that ticker symbols use common abbreviations and, for that reason, have a higher chance of overlap. These are ticker symbols with a generic context such as "T", "ON", "APA" and "COST" in the dataset. Moreover, next to the ticker symbols that make use of letters from the alphabet, Asian Stock exchanges, such as the Hong Kong Stock Exchange and the Shanghai Stock Exchange, use ticker symbols that only provide a code in numbers ranging from four to six digits. For example, the Japanese company Toyota uses the ticker symbol "7203" on the Tokyo Stock Exchange. Therefore, searching for an Asian ticker code could also give biased information as a Google search user could search a random set of numbers for other purposes.

As this research focuses on the global stock market following the MSCI World Index, there are many different combinations of tickers from Western and Asian Stock Exchanges. For this reason, this thesis will focus on both the company names and ticker symbols to identify investor attention in a certain stock after considering the above advantages and disadvantages.

For the company names, the focus will be on the official names that have a realistic fit for a search query, mostly excluding the legal form such as "Inc." or "LTD" (Swamy et al., 2019). Sometimes, the legal form is needed to explain the specific entity of a global company. For example, there are four different entities of Unilever in the data sample. Therefore, it is chosen to keep "Unilever NV" and "Unilever plc" as separate keywords as they are traded separately, and investors could have separate attention for both stocks.

Moreover, noisy keywords that could lead to abnormal higher search results will not be eliminated as the data sample of 1317 firms is too large to flag all noisy keywords manually. It could also lead to a survivorship bias in the data sample. Furthermore, noise will be smoothed out as both the results of company names and ticker symbols will be compared. When the search query of either the company name or ticker symbol will give an abnormal high difference in results, they will be eliminated.

Most of the companies in the data sample have frequent data on Google Trends due to the high market value. The weekly GSV shows the number of searches for a term scaled by its time-series average for each specific search query. The descriptive statistics of investor attention measured by GSV can be found in Table 5.

Table 5 – GSV descriptive statistics by year

Table 5 provides the descriptive statistics for the control variables per year. The table shows the mean and standard deviation values for Tobin's Q, turnover, and leverage. The descriptive statistics range from 2013 to 2019, where N is the number of observations and firms the number of firms.

Table 5 - GSV descriptive statistics by year

	GSV Ticker (Std.)		GSV Company Name (Std.)		GSV Composite (Std.)	
	Mean	SD	Mean	SD	Mean	SD
2013	0.309	1.186	0.354	1.150	0.329	0.879
2014	0.411	1.149	0.343	1.118	0.375	0.862
2015	-0.172	0.951	-0.041	1.001	-0.108	0.738
2016	-0.181	0.847	-0.272	0.857	-0.225	0.640
2017	-0.124	0.810	-0.178	0.819	-0.150	0.617
2018	-0.128	0.844	-0.147	0.855	-0.137	0.649
2019	-0.114	0.945	-0.058	0.947	-0.083	0.729
All	0.000	0.999	0.000	0.999	0.000	0.771
N	466,284		457,912		477,932	
Firms	1,281		1,258		1,313	

4 METHODOLOGY

This section elaborates on which methods will be used to obtain accurate results for stock performance. Firstly, the choice of asset pricing models will be explained. Secondly, the specific use of Granger causality tests within this thesis will be explained in the performance evaluation section. Moreover, the performance outline of both the single sort and the double sort approach will be described, including its implications. Furthermore, the use of panel regressions, the vector autoregression (VAR) model, and Granger causality tests as extensive analyses will be explained.

4.1 Asset pricing model

The following section explains which asset pricing models measure the constructed portfolios' outperformance in this research.

Asset pricing models are used in this thesis to understand better how ESG factors and investor attention (measured by GSV) affect stock performance. Factor models price assets based on their exposure to certain risk factors. In this research, theories of Fama and French (1993) complemented Carhart (1997) are used to construct the four-factor model as asset pricing model. Hereby the risk factors of the Fama and French (1993) three-factor model and momentum factor of Carhart (1997) are assessed to determine the alphas and calculate the risk-adjusted excess returns of the constructed portfolios. More specifically, this research compares Jensen's alphas of the Fama and French three-factor model and the Carhart four-factor model with the alphas of the Capital Asset Pricing Model (CAPM). By comparing both models' alphas, we can see which model outperforms after controlling for its risk factors.

The following paragraphs will explain the pricing models, including its factors used, in detail. Moreover, the chosen model use will be elaborated for its specific use. Linter (1965) and Sharpe (1964) build further on the portfolio model by Markowitz (1952) by introducing the CAPM. The CAPM clarifies the required rate of return of an asset to determine how diversified a portfolio is. The CAPM is determined by:

$$R_{it} - r_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - r_{ft}\right) + \varepsilon_{it} \tag{1}$$

Where the CAPM takes systematic risk, the beta, into account, which cannot be diversified. The beta is a measure of risk by showing how sensitive the expected return of a stock is to the market's return (Fama and French, 2004). The dependent variable in the CAPM time-series regression is excess returns ($R_{it} - R_{ft}$), which is the average excess return of the portfolio minus the average risk-free rate. The risk-free rate (r_{ft}) is determined by the return on a one-month Treasury bill. Moreover, the CAPM consists of the firm-specific alpha (α_i), the portfolio beta (β_{iM}), the market risk $\left(R_{Mt} - r_{ft}\right)$, and the error term ε_{it}. Here *i* is the portfolio and *t* the time period per month.

Moreover, Jensen (1968) was the first to introduce the intercept term α_i, also Jensen's alpha, in the time-series regression. Jensen's alpha shows the risk-adjusted performance by the average return of a portfolio relative to what is predicted by the CAPM. An alpha above zero shows that a portfolio outperforms due to higher excess returns. Vice versa, an alpha below zero shows underperformance for a certain portfolio.
The formula of Jensen's alpha can be found beneath:

$$\alpha_J = R_i - [R_f + \beta_{iM} * \left(R_M - R_f\right)] \tag{2}$$

Where Jensen's alpha (α_J) is determined by R_i, the portfolio return for portfolio *i*. Again, β_{iM} is the portfolio beta and $R_M - R_f$ is the market risk measured by the market return minus the risk-free rate.

The Fama and French three-factor model extends the CAPM that accounts for market risk by adding company size and value factors with the respective Small Minus Big (SMB) and High Minus Low (HML) factors to account for its risks. Therefore, Fama and French (1992) account for the three factors market risk, size and value. They find a negative relationship between size (market value of equity) and excess returns. This indicates that large firms have lower excess returns on average than small firms, resulting in the outperformance of small market cap stocks. Moreover, a positive relationship is found between value (book-to-market ratio of equity) and excess return, both in cross-sectional regressions. This indicates that value (high book-to-market equity ratio) firms have higher excess returns relative to growth (low book-to-market equity ratio) firms, resulting in the outperformance of low price to book stocks. To account for these anomalies, Fama and French (1993) add the size (SMB) and value (HML) factors to the CAPM, resulting in the three-factor asset pricing model:

$$R_{it} - rf_t = \alpha_i + \beta_{1i}(R_{mt} - rf_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \epsilon_{it} \tag{3}$$

Additionally, for the Carhart four-factor model, an extra momentum (MOM) factor for stocks' asset pricing is added to the model. Carhart (1997) added the momentum risk factor to Fama and French's (1993) three-factor model after Jegadeesh and Titman (1993) found a one-year momentum anomaly. Chan et al. (1996) explain that momentum anomaly is a market inefficiency due to slow reaction to information. Carhart (1997) explains that portfolios consisting of past winners are more likely to have higher excess returns than past losers. The risk factor momentum is added to the three-factor model

accounting for one-year momentum in stock returns to control for this. The risk factor is determined by the monthly premium on winners minus losers.
The Carhart (1997) four-factor asset pricing model:

$$R_{it} - rf_t = \alpha_i + \beta_{1i}(R_{mt} - rf_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \varepsilon_{it} \quad (4)$$

When focusing on the Carhart four-factor model as a whole: again, the dependent variable in the model is the excess return showed by the variable $R_{it} - rf_t$, which shows the return of portfolio *i* in month *t* in excess of the risk-free rate in month *t*. For the independent variables, the coefficients $\alpha_i, \beta_{1i}, \beta_{2i}, \beta_{3i}$, and β_{4i} are alpha, and all the portfolio betas for each risk factor are estimated following an ordinary least squares (OLS) regression. Moreover, the risk factors are market risk premium, SMB, HML, and MOM. They represent the monthly premium value of returns on value-weighted and zero-investment portfolios for size, value (book-to-market factor), and momentum (winners minus losers) in month *t*. The error term is reflected by ε_{it} which is assumed to be zero with $Variance\ (\varepsilon_{it}) = \varepsilon_{\varepsilon}^{2}$. The regressions are performed by applying Newey and West's (1987) standard errors to control for serial autocorrelation and heteroskedasticity.

Important to note is that all risk factors are zero-investment portfolios. SMB goes long on small-cap stocks and short on big-cap stocks. Furthermore, HML goes long on high book-to-market stocks and short on low book-to-market stocks. Additionally, MOM longs previous 12-month return winners and shorts previous 12-month loser stocks. Hereby, the portfolio's overperformance will be compared with the performance expected based on the asset pricing model. A positive alpha indicates that the ESG portfolio performed better than expected given its exposure to the various risks considered in the asset pricing model.

As explained above, the Carhart momentum four-factor model is used in this research. This choice is based on the added momentum factor that controls for premium on winners' stocks relative to losers. Moreover, Blitz et al. (2018) advise on the disadvantages of Fama and French's (2015) five-factor model. The five-factor model has added two extra risk factors to its traditional three-factor model to explain stock returns. The first risk factor is profitability, which controls for the superior performance of high operating profitability stocks. Secondly, an investment risk factor is added, which controls for the different returns of low and high investment firm stocks. Blitz et al. (2018) argue that adding those two new factors will not explain returns better. The profitability and investment factors are relatively new findings and will only explain their own performance. Moreover, the five-factor model as a whole will explain the returns of the same five factors more. Therefore, adding extra risk factors does not say it will result in more accurate returns. Blitz et al. (2018) argue that the five-factor model does not account for momentum and low volatility. Therefore, taking the above into account, the Carhart (1997) four-factor model is used as main asset pricing model in this research.

Additionally, this thesis performs the GRS-test, founded by Gibbons, Ross, and Shanken (1989), to test a given portfolio's efficiency. The GRS-test's objective is to determine which asset pricing model is the most efficient in explaining the alphas. The test will be used to test whether the expected value of the six intercepts is jointly equal to zero. The GRS test will be performed to judge model performance after determining the efficiency per portfolio. This research compares the efficiency of the CAPM and the Carhart four-factor model. The GRS test statistic is:

$$\frac{(T-N-K)}{N}\left(\frac{\hat{\alpha}'\widehat{\Sigma^{-1}}\,\hat{\alpha}}{1+\bar{\mu}'\widehat{\Omega^{-1}}\,\bar{\mu}}\right)\sim F(N,T-N-K) \tag{5}$$

Where T is the number of time-series observations, N is the number of assets or portfolios, K is the number of factors. Further, $\hat{\alpha}$ is a N x 1 vector of the estimated intercepts, $\hat{\Sigma}$ is the unbiased estimated variance-covariance matrix of the intercepts. $\bar{\mu}$ is a K x 1 vector of the factor portfolios' sample means, and $\hat{\Omega}$ is the factor portfolios' unbiased estimated variance-covariance matrix.

Moreover, the Sharpe ratio is calculated to evaluate each portfolio's individual performance as an extra check next to the asset pricing models. The Sharpe ratio is widely used in research as a portfolio performance measure since it accounts for risk-adjust returns (Sharpe, 1994). A higher Sharpe ratio measures the outperformance of a portfolio. The Sharpe ratio is calculated the following:

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p} \tag{6}$$

Where portfolio return (R_p) minus the risk-free rate (R_f) is divided by the standard deviation (σ_p) of the portfolio's excess return. The standard deviation shows how the portfolio's return deviates from the expected return, hereby taking volatility into account.

Additionally, the Sharpe ratios' statistical difference is determined following the performance hypothesis testing of Memmel (2003). The test statistic Z shows if the top portfolio Sharpe ratio differs statistically from the bottom portfolio Sharpe ratio. This research uses the test statistic following Memmel (2003):

$$z_{JK} = \frac{\hat{S}h_i - \hat{S}h_n}{\sqrt{\hat{V}}} \tag{7}$$

Where $\hat{S}h_i - \hat{S}h_n$ is the sample differences for two portfolios i and n and $\hat{V}$ is the asymptotic variance of the Sharpe ratio difference in the numerator, of the test statistic, z_{JK}.

4.2 Performance evaluation

This thesis aims to find whether stocks outperform due to their ESG rating or due to investor attention around its stock. Normally, Granger causality is a required condition at the start of empirical research to may sort for, in this case, ESG and investor attention. The initial research design was to perform Granger causality tests at the beginning of this thesis. However, this research faces the problem of a difference in data frequency. ESG data is available yearly, and investor attention measured by Google search is available weekly. Performing Granger causality tests on ESG and investor attention will give distorted results due to the disparity in data frequency. Especially for ESG, the ESG scores are available per year, which is too little information to explain the many fluctuations in prices, and hence returns. Therefore, this thesis's research design chooses to determine the relation between stock returns and investor attention (GSV) and how this relationship changes due to firms' ESG-rating. As a result, the Granger causality tests are only possible combined with the vector autoregression (VAR) model in the last section of the performance evaluation chapter.

Hence, the performance evaluation is structured as follows. Firstly, the standalone effect of both ESG and investor attention is assessed in a single sorting approach. ESG is single sorted to find if high ESG firms outperform low ESG firms. Furthermore, investor attention is single sorted in GSV portfolios to test whether high attention firms outperform low attention firms. Secondly, both interaction measures are combined in a double sorting approach to determine which aspect has an additional effect on the other. Finally, a panel regression, vector autoregression, and Granger causality tests are performed to determine the relation of stock returns and investor attention and how high-rated ESG firms affect this relation. Important note: for all hypotheses tested in this research, a two-sided test is performed as all regressions will be examined conservatively on significance ($t > 1.96$) as well as the sign of the coefficient.

4.2.1 Single sort ESG

The first aim of this thesis is to evaluate the standalone effect of ESG performance on its stock performance of portfolios. Therefore, the first hypothesis stated below will be tested in the results section.

***H1**: "High-rated ESG firms have higher risk-adjusted returns than low-rated ESG firms."*

To test the above hypothesis, ESG portfolios are constructed in terciles and deciles based on their low to high ratings. This thesis's portfolio construction is conducted following how Fama and French (1993) create their risk factors. All firms in the data sample are divided into terciles based on their yearly ESG score. The terciles are divided equally into three parts at the beginning of each year, which will give three equal-sized dynamic portfolios. The portfolios are called ESG1 (low ESG scores), ESG2 (medium ESG scores), and ESG3 (high ESG scores). Additionally, another portfolio is constructed to measure if high ESG firms outperform low ESG firms. This portfolio is the high ESG portfolio minus the low ESG portfolio, called HMLESG. The latter portfolio is a zero-investment strategy portfolio indicating going long in the high ESG firms and going short in low ESG firms. Moreover, next to the terciles, another portfolio construction in deciles is conducted to see the closer effects of ESG scores on stock performance. Again, ESG1 is the lowest ESG portfolio with the bottom 10% ESG scores, and ESG10 the highest ESG portfolio with the top 10% ESG scores. The high minus low portfolio is here HMLESG.

Furthermore, the Carhart four-factor model is used to measure the out- or underperformance based on the sign of alpha of each ESG portfolio. The objective is to find if high ESG portfolios outperform, due to positive alpha, relative to low ESG portfolios. This research will first look at ESG portfolios constructed in terciles. Subsequently, it will dive deeper into the specific effects of having a higher ESG rating by constructing ten portfolios based on its ESG rating. Next to the determination of alphas to discover outperformance, the performance will be evaluated using the Sharpe ratio for each portfolio. A higher ratio indicates portfolio outperformance relative to other portfolios. Lastly, the statistical difference between the Sharpe ratios is determined following Memmel (2003).

4.2.2 Single sort investor attention

The second aim of this thesis is to evaluate the standalone effect of investor attention on the stock performance of portfolios. Therefore, the second hypothesis stated below will be tested in the results section.

***H2**: "Firms with low investor attention have higher risk-adjusted returns than high investor attention firms."*

To test the above hypothesis, investor attention is divided into ticker, company name, and composite Google searches, resulting in the three below hypotheses to test each separate effect:

> ***H2a**: "Firms with low investor attention by ticker searches have higher risk-adjusted returns than high investor attention firms."*
>
> ***H2b**: "Firms with low investor attention by company name searches have higher risk-adjusted returns than high investor attention firms."*

H2c: "Firms with low investor attention by composite searches have higher risk-adjusted returns than high investor attention firms."

To test the above hypotheses, the performance evaluation of the single sort approach for investor attention is exactly the same as the single sort approach of ESG. However, instead of ESG, the portfolios are constructed based on search query data of Google Trends. Hereby the Google Search Volume (GSV) factor is used within the model to determine the effect of investor attention. GSV portfolios are constructed by first calculating a standardized GSV as in equation (8) to make indices more comparable across firms (Swamy et al., 2019). The standardized value of GSV is calculated:

$$GSV_t = \frac{GSV_{it} - \frac{1}{n}\sum_{i=1}^{n} GSV_i}{\sigma_{GSV}} \tag{8}$$

To elaborate on the above equation (8), *n* is the number of weeks of GSV observations and σ_{GSV} is the total sample standard deviation of the GSV time series. Thus, the standardized value of GSV is (GSV value minus GSV average) divided by the standard deviation of the GSV time series, indicating that the standardized GSV always has a mean of 0.

Swamy et al. (2019) explain that the above equation has several characteristics and therefore needs some explanation:

1. The value of GSV depends on the number of searches for a particular query relative to all other search queries completed in the same period.
2. GSV shows a relative value between 0 and 100, as the weekly GSV shows the number of searches for a term scaled by its time-series average for each specific search query.
3. The value of GSV does not rise when the number of searches for a particular query is lower relative to other queries.

Furthermore, investor attention data is gathered for both ticker and company name Google searches. Portfolios are constructed for both attention measures to disentangle the effects of both company name searches and ticker symbol searches on returns. Moreover, a composite portfolio is constructed to assess the combined effect of GSV on returns, which is the average standardized GSV value of company name and ticker symbol searches. For all three portfolios, company name, ticker symbol, and composite, the choice of portfolio construction in terciles and deciles is conducted. Again, GSV1 is the lowest standardized GSV value, and GSV3 and GSV10 are the highest standardized GSV value. The choice for both terciles and deciles is to compare more general with more specific results. Again, the HMLGSV portfolios are added to construct the zero-investment high minus low portfolios.

Important to note is that the GSV portfolios are based on monthly standardized GSV values. This indicates that the portfolios are dynamically constructed every month. As GSV data is available every week, the mean weekly standardized values are taken to construct the dynamic GSV portfolios on a monthly basis. This means that the firms can change GSV groups every month. The particular choice for this construction is that it gives more accurate results because each portfolio reinvests every month in a certain tercile/decile. If the portfolios were constructed dynamically per week, an active reinvestment bias could occur for portfolio construction. On the other hand, yearly GSV portfolios will be constructed based on their mean standardized GSV value in the first week of the year. This will give distorted results of actual investor attention measured by GSV.

4.2.3 Double sorted ESG – GSV portfolios

In the previous sections, the single sort of both ESG and GSV constructed portfolios are conducted to measure the separate effect of ESG scores and investor attention on returns. This section will combine both single sorted methods by applying a double sorting approach. To measure the additional effect of investor attention on stock performance, the ESG portfolios are constructed in the same way as the single sort method above. Moreover, Google Trends' data, Google Search Volume (GSV), is added to the model to determine investor attention's additional effect. The objective is to find the driving force of both ESG and investor attention and its effect on returns. This will be done by applying a double sorting approach to the method. Therefore, the third hypothesis stated below will be tested in the results section.

***H3**: "High-rated ESG firms and firms with low investor attention have the highest risk-adjusted returns relative to the other combinations."*

Again, investor attention is divided into ticker, company name, and composite Google searches to test the above general third hypothesis. This results in the three below hypotheses to test each separate effect:

> ***H3a**: "High-rated ESG firms and firms with low investor attention by ticker searches have the highest risk-adjusted returns relative to the other combinations."*
>
> ***H3b**: "High-rated ESG firms and firms with low investor attention by company name searches have the highest risk-adjusted returns relative to the other combinations."*
>
> ***H3c**: "High-rated ESG firms and firms with low investor attention by composite searches have the highest risk-adjusted returns relative to the other combinations."*

The positive effect of investor attention could imply that higher investor attention explains higher returns for ESG portfolios. The objective is to find the additional effect of investor attention on ESG constructed portfolios by disentangling both effects. This research sorts the stocks in the three dynamic groups (low, medium, and high) for both effects. For ESG scores, this is done on a yearly basis as ESG scores are only available each year. For investor attention, monthly average values are taken from the weekly data, which is in line with the single sort GSV method. After double sorting the independent stocks on both characteristics (3 x 3), there will be formed 9 portfolios on each possible combination of ESG and investor attention. Again, a double sorting is conducted for the two investor attention measures, ticker symbol and company and the combined, composite GVS, attention measure.

The Carhart four-factor model is used to calculate the alphas compared with the CAPM to assess the excess returns. The objective of the double sorting approach is to evaluate the performance of each possible combination. Therefore, high, medium, and low groups are formed for both effects to assess double sort outperformance after having conducted the single sort approach. This research aims to find the outperforming combination due to the double sorting approach. It could be that high ESG and high investor attention outperforms. Alternatively, it could be possible that high ESG and low investor attention outperform instead. This will be tested and become more evident in the results section.

4.2.4 Panel regressions

In the above sections, performance is evaluated by the single and double sorting approaches after portfolio construction within the asset pricing model framework. The asset pricing model takes mean values to construct each portfolio for ESG factors yearly and GSV values monthly. The main limitation of this method is that the average return of many firms is taken per period. Therefore, the direct effect of both factors on performance is difficult to measure, especially for ESG. As the ESG factors are based on yearly information, the relation of ESG on performance is difficult to interpret in the asset pricing sorting approaches. This is mainly because the many price fluctuations cannot be explained by that firm's yearly ESG score. Moreover, plenty of information is lost for GSV because the mean values are taken for a factor with a short-term effect on performance. Therefore, a more appropriate method to measure ESG and GSV's direct effect on the performance is to run a lagged panel regression. Hereby we look at the relation between expected returns and GSV for different types of companies sorted on their ESG score. A panel regression will be run to examine the individual effect of investor attention on the returns, and vice versa, more accurately per ESG portfolio for the levels low, medium, and high. Therefore, the two hypotheses stated below will be tested in the fourth results section.

H4a*: "Investor attention has a significant effect on the returns in high-rated ESG portfolio."*

***H4b**: "Returns has no significant effect on investor attention in high-rated ESG portfolio."*

The following paragraphs will elaborate on the panel regression, the control variables, and the determination of optimal lags. The lagged panel regression's objective is to find the effect of investor attention per individual stock for the low, medium, and high levels of ESG. To select the correct number of lags, a general panel regression without incorporating the ESG factor is run to find the right explanatory value of the lags. Lags without explanatory value could be subject to noise. Therefore, choosing the optimal number of lags is a trade-off between a higher R-squared (explaining more in the model) versus noise and multicollinearity (less precision within the coefficients due to higher correlation between the lags). The general formula of the lagged panel regression can be found beneath:

$$E(r_{it}) = a_i + \sum_{p=1}^{P} \beta_{1t-p} GSV_{it-p} + \gamma \boldsymbol{X} + \theta_i + \tau_t + \epsilon_{it} \tag{9}$$

Here $E(r_{it-p})$ is the lagged weekly expected returns per stock *i* in period *t* with *p* as the max number of lags in the model. Expected returns are determined by the constant (a_i), lagged investor attention (GSV_{it-p}), and the added controls. Moreover, γ is the vector of coefficients for the vector of control variables $\boldsymbol{X}$, which is the vector of control variables with the appropriate number of lags. The control variables can be seen in the equation below. Furthermore, θ_i is the firm fixed effect, τ_t is the time-specific fixed effect (week fixed effects), and ϵ_{it} is the time and firm-specific error term. The panel regression estimation is performed by applying ordinary least squares (OLS) to each equation at one time. It is important to note that the dependent variable is lagged since it is plausible that its past level determines the current level of the dependent variable. Not including a lagged dependent variable will lead to an omitted variable bias.

The following formula shows the panel regression with the added control variables, which are filled in for $\gamma \boldsymbol{X}$ in equation (9).

$$\begin{aligned} E(r_{it}) = a_i + \sum_{p=1}^{P} \beta_{1p} GSV_{it-p} + \sum_{p=1}^{P} \beta_{2p} SD_{it-p} + \sum_{p=1}^{P} \beta_{3p} MV_{it-p} + \sum_{p=1}^{P} \beta_{4p} TOBQ_{it-p} \\ + \sum_{p=1}^{P} \beta_{3p} TURNOVER_{it-p} + \beta_4 LEV_{it} + \theta_i + \tau_t + \epsilon_{it} \end{aligned} \tag{10}$$

As can be seen in the above formula, the panel regression uses time and firm-specific standard deviation (SD), market value (MV), Tobin's Q (TOBQ), and turnover (TURNOVER) to control for volatility, size, the replacement value of assets, and trading volume where *p* is the max number of lags.

Sidenote: the variables market value and Tobin's Q could be interrelated to each other. Furthermore, the panel regression controls for time and firm-specific leverage (LEV) per year as the data of leverage is only available per year.

After finding the number of optimal lags, the panel regression will be run separately per ESG subsample for both expected returns and GSV as dependent variables to see how both factors affect the returns of ESG firms. These subsamples are again divided into low, medium, and high ESG levels. It is important to note that the returns per ESG portfolio are based on the four-factor model's returns as calculated in equation (4).

4.2.5 Vector autoregression model and Granger causality tests

In the previous section, the methodology of the panel regressions for returns and GSV was explained. This section will elaborate on the combination of both variables in a vector autoregression (VAR) model. Subsequently, corresponding Granger causality tests are performed to answer the hypotheses. Therefore, this section's underlying hypotheses will be testing the causality of both investor attention and returns. Hence, the hypotheses are divided into the causality of investor attention on returns (Hypothesis 5a) and vice versa, the causality of returns on investor attention (Hypothesis 5b) for high ESG portfolios. This gives us the following two hypotheses for the fifth section:

H5a*: "Investor attention Granger causes returns in high-rated ESG portfolios."*

H5b*: "Returns Granger cause investor attention in high-rated ESG portfolios."*

Firstly, the theory and the lag determination of the VAR will be explained below. Subsequently, this section describes how the VAR model will be used in this research. Finally, the above hypotheses will be divided into the three ESG levels to test each causality effect with the Granger causality tests.

The basic principle of the VAR is that there is no dependent or independent variable which indicates that an independent variable has the same explanatory value as a dependent variable. The VAR models the time series as a linear combination of its own lags. This means that the past values of the time series are used to predict current and future values. Therefore, the VAR model accounts for all variables to be jointly determined. This thesis measures if investor attention explains returns for the different levels of the ESG portfolios, and at the same time, if returns within the same ESG portfolios explain investor attention. Each variable in the VAR model is expressed as a function of its own lags while also expressed by all lags of the other variables in the model. The VAR model is characterized by the fact that every equation has exactly the same explanatory variables. The VAR estimation is simple as it applies ordinary least squares (OLS) to each equation at one time. Even though the model is a system of equations, OLS can be applied to each equation because the set of explanatory variables is the same in each equation.

To determine the lags in the VAR, information criteria tests will be conducted following the paper of Abrigo and Love (2016) by minimalizing the Akaike information criterion (AIC), Bayesian information criterion (BIC), Hannan-Quin information criterion (HQIC). Andrews and Lu (2001) proposed moment and model selection criteria (MMSC) for generalized method of moments models based on Hansen's (1982) J statistic of overidentifying restrictions. Their proposed MMSC are analogous to various commonly used maximum likelihood-based model-selection criteria, namely, the AIC (Akaike, 1969), the BIC (Schwarz, 1978; Rissanen, 1978; Akaike, 1977), and the HQIC (Hannan and Quinn, 1979). Their proposed criteria select the pair of vectors (p, q) that minimizes:

$$MMSC_{BIC,n}(k,p,q) = J_n(k^2p,k^2q) - (|q| - |p|)k^2 \ln n \tag{11}$$

$$MMSC_{AIC,n}(k,p,q) = J_n(k^2p,k^2q) - 2k^2(|q| - |p|) \tag{12}$$

$$MMSC_{HQIC,n}(k,p,q) = J_n(k^2p,k^2q) - Rk^2(|q| - |p|) \ln \ln n \quad R > 2 \tag{13}$$

Where $J_n(k,p,q)$ is the J statistic of overidentifying restriction for a k-variate panel VAR of order p and moment conditions based on q lags of the dependent variables with sample size n. In short, these mathematical information tests evaluate how well the model fits the data. The lowest value of the criteria test shows the best fit for the model.

Moreover, the VAR forms the basis to perform Granger causality tests, explaining the determination of explanatory value per variable. This will be conducted in the following section to determine how ESG and GSV are related to each other and which variable reinforces each other. Earlier research by Barber and Odean (2008) showed that stocks are short-term inflated followed by lower returns due to investor attention. The VAR model in this thesis studies if the same effect of investor attention can be measured for ESG stocks. Therefore, the following two equations have been constructed to estimate the two VAR models.

$$E(r_{it}) = a_i + \sum_{p=1}^{P} \beta_{1p} GSV_{it-p} + \sum_{p=1}^{P} \beta_{2p} E(r_{it})_{it-p} + \gamma \boldsymbol{X} + \theta_i + \tau_t + \epsilon_{it} \tag{14}$$

$$GSV_{it} = a_i + \sum_{p=1}^{P} \beta_{1p} GSV_{it-p} + \sum_{p=1}^{P} \beta_{2p} E(r_{it})_{it-p} + \gamma \boldsymbol{X} + \theta_i + \tau_t + \epsilon_{it} \tag{15}$$

The first VAR model estimates the OLS regression with expected returns as dependent variable in equation (14), whereas the second equation (15) uses GSV as dependent variable.
The dependent variables in equations (14) and (15), expected returns ($E(r_{it})$) and (GSV_{it-p}), are lagged in lag p per stock *i* in period *t.* Both dependent variables are determined by the constant (a_i), lagged investor attention (GSV_{it-p}), lagged expected returns ($E(r_{it})_{it-p}$) and γ, the vector of coefficients for the vector of control variables $\boldsymbol{X}$, which is the vector of control variables with the appropriate number of lags. Factor $\boldsymbol{X}$ consists of the unlagged controls, consistent with the variables used in equation (10), which are SD, MV, TOBQ, Turnover, and LEV. Furthermore, θ_i is the firm fixed effect, τ_t is the time-specific fixed effect (week fixed effects), and ϵ_{it} is the time and firm-specific error term, which is considered white noise. The estimation of the vector autoregression (VAR) model is performed by simply applying ordinary least squares (OLS) to each equation at one time.

Moreover, the vector autoregression (VAR) model forms the basis to perform Granger causality tests. Granger causality tests are used in research to find the causal relationship between two variables. Building further on the VAR, Granger causality tests will be performed to find the causal relationship between GSV and expected returns.

Granger causality is a statistical hypothesis test that predicts the causality between two variables rather than measuring the correlation between variables. The test tries to explain a certain time series by using a historical time series. With a Granger causality test, when variable X_1 "Granger-causes" variable X_2, then past data of variable X_1 has a forecasting effect on variable X_2 besides of the forecasting data variable X_2 already holds (Granger, 1969). The Granger causality tests' objective is to determine which variable comes before the other in the time series. The Granger causality tests have the same regressions as the VAR. Therefore, the VAR equations (14) and (15) are used to examine if the lags of all the coefficients together can explain the dependent variable for a given variable.
The parameter ϵ_{it} is the uncorrelated white noises prediction error for each time series. If $E(r)$ "Granger-causes" GSV (or vice versa), then the coefficients of β are jointly significantly different from zero. In this research, the test is performed by applying a chi-square test of the null hypothesis to find Granger causality. The optimal number of lags determines the degrees of freedom. The variable "Granger-causes" another variable when the probability value shows a significant value for the null hypothesis.

5 RESULTS

In line with this paper's research design, this chapter provides an overview of the results structured per hypothesis.

5.1 Single sort ESG

The first aim of this thesis is to evaluate the standalone effect of ESG performance on its stock performance of portfolios. Therefore, this first section tests the below-stated hypothesis.

***H1**: "High-rated ESG firms have higher risk-adjusted returns than low-rated ESG firms."*

Tables 6A and 6B show the results of the single sorted ESG constructed portfolios for the CAPM and four-factor model in terciles and deciles. This paper studies the results for ESG portfolios constructed in terciles and in deciles for robustness.

Table 6A shows the results for the portfolios ESG1, ESG2, ESG3, and HMLESG. These are the low, medium, high, and high minus low portfolios with a respective average ESG score of 34.68 (low), 59.17 (medium), and 78.00 (high). Table 6A shows that the CAPM and the four-factor model both have the same alphas. The alphas of ESG1 and ESG2 are positive and significant in the CAPM. Furthermore, the four-factor model shows positive and significant values for all three alphas, including ESG3, within a 10% significance level. Compared to the CAPM, every portfolio outperforms in the four-factor model. However, ESG1 is the most significant, under a 1% significance level, for both asset pricing models with an alpha of 0.2%. This indicates that low ESG firms outperform high ESG as they have higher alphas. Moreover, the high minus low (ESG4) portfolio is added to show the clear difference between both portfolios. HMLESG shows a negative alpha of 0.1% under a significance level of 1%. This means that the low ESG portfolio significantly outperforms the high ESG portfolio, hence having a more significant effect on returns.

The following will describe the different risk factors more specifically. It can be seen that the market risk premium ($R_m - R_f$) is positive and significant for all portfolios in both the CAPM as the four-factor model. The market risk premium holds for systematic risk, which explains the returns for movements in the market. The SMB risk-factor is positive and significant for ESG1 under a 5% significance level and ESG2 under a 10% significance level, while ESG3 is also positive but not significant. The risk-factors HML and MOM do not have any significant values. This means that the risk factors are not statistically different from zero for firms with a higher book-to-market ratio and past winning stocks. However, when testing the GRS statistics, both the CAPM and the four-factor model display p-values close to zero, which would indicate that both models should be rejected as they are not efficient.

Moreover, the Sharpe ratio is measured as an extra performance check. In Table 6A, the Sharpe ratio decreases from 3.717 for ESG1 to 2.471 for ESG3. In Table 6B, the Sharpe ratio decreases from 3.709 for ESG1 to 1.959 for ESG10. Moreover, testing the statistical difference of the top and bottom portfolios (HMLESG) results in a significant test statistic of -3.392 (Table 6A) and -2.988 (Table 6B) under a significance level of 1%. This implies that low ESG portfolios statistically outperform high ESG portfolios. Therefore, a contrarian investing strategy is more profitable, implying one should invest in an LMH portfolio.

In short, the low ESG portfolio significantly differs from the medium and high ESG portfolio after adjusting for risk. There is significant evidence to reject Hypothesis 1 based on the above results. This indicates that high-rated ESG firms do not outperform relative to low-rated ESG firms.

Table 6A: Single sort ESG portfolio for CAPM & four-factor model (Terciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for ESG portfolios constructed terciles. The terciles, ESG1 (Low), ESG2 (Medium), and ESG3 (High) are equally divided based on their mean ESG rating (Mean ESG). Moreover, the High minus Low (HMLESG) reflects the zero-investment strategy portfolio, which takes a long (short) position in the high (low) ranked firms in terms of their respective ESG score. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. Sharpe ratio is presented per individual portfolio, including Memmel's (2003) Z statistic to test the statistical difference for the HMLESG portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

	ESG Portfolio Alpha (No. of quantiles = 3) (CAPM)			
	ESG1	ESG2	ESG3	HMLESG
Alpha	0.002***	0.002**	0.001	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.515***	0.533***	0.553***	0.038*
	(0.07)	(0.07)	(0.07)	(0.02)
GRS	9.336***	6.432**	2.434	15.684***
Sample (N)	363	363	363	363
R-squared	0.281	0.304	0.314	0.014
Adj R-squared	0.279	0.303	0.312	0.011
F	51.01***	61.69***	72.23***	3.49*
	ESG Portfolio Alpha (No. of quantiles = 3) (4-factor model)			
	ESG1	ESG2	ESG3	HMLESG
Alpha	0.002***	0.002**	0.001*	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.538***	0.547***	0.556***	0.018
	(0.07)	(0.07)	(0.07)	(0.02)
SMB	0.326**	0.230*	0.204	-0.121***
	(0.14)	(0.13)	(0.13)	(0.05)
HML	0.032	0.087	0.098	0.067
	(0.12)	(0.11)	(0.12)	(0.04)
MOM	0.048	0.041	-0.020	-0.068**
	(0.07)	(0.07)	(0.08)	(0.03)
GRS	9.480***	6.694***	2.991*	13.400***
Sharpe Ratio	3.717	3.282	2.471	-3.715
SR test Z				-3.392***
Sample (N)	363	363	363	363
R-squared	0.298	0.313	0.323	0.088
Adj R-squared	0.290	0.306	0.315	0.077
F	14.72***	17.86***	20.16***	8.30***
Mean ESG	34.68	59.17	78.00	.

Table 6B: Single sort ESG portfolio for CAPM & four-factor model (Deciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for ESG portfolios constructed deciles. The deciles, ESG1 (Low) up to ESG10 (High) are equally divided based on their mean ESG rating (Mean ESG). Moreover, the High minus Low (HMLESG) reflects the zero-investment strategy portfolio, which takes a long (short) position in the highest (lowest) ranked firms in terms of their respective ESG score. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. Sharpe ratio is presented per individual portfolio, including Memmel's (2003) Z statistic to test the statistical difference for the HMLESG portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

ESG Portfolio Alpha (No. of quantiles = 10) (CAPM)											
	ESG1	ESG2	ESG3	ESG4	ESG5	ESG6	ESG7	ESG8	ESG9	ESG10	HMLESG
Alpha	0.002***	0.002***	0.002***	0.002**	0.002***	0.002**	0.002**	0.002**	0.001	0.001	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.517***	0.492***	0.530***	0.545***	0.542***	0.527***	0.515***	0.510***	0.569***	0.593***	0.076**
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.03)
GRS	9.309***	10.564***	9.118***	5.521**	7.302***	5.412**	5.515**	5.097**	1.523	0.898	13.508***
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.261	0.265	0.291	0.298	0.301	0.289	0.295	0.296	0.311	0.313	0.022
Adj R^2	0.259	0.263	0.289	0.296	0.299	0.287	0.293	0.294	0.309	0.311	0.020
F	44.63***	47.70***	56.85***	60.72***	64.62***	56.79***	59.74***	68.19***	72.13***	74.86***	6.11**
ESG Portfolio Alpha (No. of quantiles = 10) (4-factor model)											
	ESG1	ESG2	ESG3	ESG4	ESG5	ESG6	ESG7	ESG8	ESG9	ESG10	HMLESG
Alpha	0.002***	0.002***	0.002***	0.002**	0.002***	0.002**	0.002**	0.002**	0.001	0.001	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.544***	0.514***	0.551***	0.562***	0.555***	0.543***	0.526***	0.524***	0.562***	0.590***	0.047
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.03)
SMB	0.381***	0.319**	0.299**	0.275**	0.251*	0.208	0.195	0.185	0.188	0.231*	-0.149**
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.07)
HML	0.071	-0.005	0.003	0.084	0.092	0.076	0.105	0.088	0.113	0.097	0.026
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)	(0.12)	(0.06)
MOM	0.068	0.034	0.038	0.044	0.029	0.055	0.036	0.057	-0.070	-0.060	-0.128***
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.04)
GRS	9.567***	10.654***	9.150***	5.779**	7.759***	5.443**	5.842**	5.139**	2.254	1.396	11.371***
SR	3.709	3.882	3.687	3.122	3.421	3.098	3.120	3.043	2.195	1.959	-3.351
SR test Z											-2.988***
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.282	0.282	0.305	0.310	0.311	0.296	0.302	0.303	0.322	0.325	0.076
Adj R^2	0.274	0.274	0.298	0.302	0.303	0.289	0.294	0.295	0.315	0.317	0.066
F	13.68***	13.19***	15.86***	17.89***	18.40***	16.45***	17.16***	19.04***	20.33***	20.99***	6.06***
Mean ESG	20.56	35.24	43.65	50.63	56.43	61.95	67.46	72.71	78.30	85.92	.

5.2 Single sort investor attention

The second aim of this thesis is to evaluate the standalone effect of investor attention on the stock performance of portfolios. Therefore, this results section states the second hypothesis:

***H2**: "Firms with low investor attention have higher risk-adjusted returns than high investor attention firms."*

The Google Search Volume (GSV) is calculated in a standardized value for each stock based on the ticker symbol and company name separately to measure investor attention. The investor attention effect on stock performance is measured by constructing GSV portfolios from low to high based on their standardized GSV value. Firstly, the ticker and company name portfolios are measured separately. The average of the ticker and company name's standardized values are taken to construct composite GSV portfolios. The separate portfolios are constructed to disentangle the individual effects of ticker symbol and company name searches and their effect on stock returns. Secondly, the composite portfolios are constructed to obtain an overall effect of investor attention on portfolio returns.

Again, this research chooses to construct portfolios in terciles and deciles. This study first investigates the terciles to get a clear overview between low and high investor attention. Moreover, this thesis dives deeper into the deciles to determine the closer effects of investor attention.

To test the above hypothesis, investor attention is divided into ticker, company name, and composite Google searches, resulting in the three below hypotheses to test each separate effect. Therefore, the following subsections will review the results for ticker, company name, and composite searches, respectively, in Tables 7, 8, and 9.

5.2.1 Ticker Google Searches

Firstly, the results of ticker Google searches will be reviewed in the single sort investor attention.

> ***H2a**: "Firms with low investor attention by ticker searches have higher risk-adjusted returns than high investor attention firms."*

Table 7A shows the GSV results of ticker searches and their effect on portfolio returns in terciles. The table shows that GSV1 is the low attention portfolio and GSV3 the high attention portfolio with a respective average standardized value of -0.812 (GSV1) and 0.867 (GSV3). The high minus low portfolio (HMLGSV) is added again to obtain an immediate result at first glance of outperformance. Here can be seen immediately that HMLGSV is slightly positive and significant. This means that high ticker GSV portfolios outperform low ticker GSV portfolios. However, if the low (GSV1), medium (GSV2), and high (GSV3) portfolios are investigated separately, it can be seen that all alphas for both CAPM as the four-factor model have a positive and significant value of 0.2%. As this seems odd, the deciles will be evaluated to look at the closer effects.

Table 7B shows the results of ticker GSV in decile constructed portfolios. Here GSV1 up to GSV7 are positive and weakly significant under 5% and 10% significance levels. Moreover, GSV8 up to GSV10 show positive and strong significant alphas for both the CAPM and the four-factor model under a 1% significance level. Moreover, the high minus low (HMLGSV) portfolio gives a positive and significant alpha of 3.7%. Again, this indicates that high ticker GSV portfolios outperform relative to low ticker GSV portfolios.

The following paragraph elaborates briefly on the effects of the different risk factors. Table 7B shows that the market risk premium is positive and significant for all portfolios in both asset pricing models. This indicates that the systematic risk explains market movement returns, which is plausible. Moreover, the SMB risk factor shows different effects per portfolio. GSV1 and HMLGSV (for both terciles and deciles) are not significant, whereas the rest is significant under 5% and 10% significance levels. The HML risk factor shows no significant values, which indicates no significant effect of the HML risk factor. The MOM risk factor only shows a significant value of 4.3% for HMLGSV in Table 7A (terciles) and has no single significance in Table 7B (deciles). This indicates that the momentum risk-factor only has a significant effect in the high minus low constructed portfolio. This means that the risk factors are not statistically different from zero for firms with a higher book-to-market ratio and past winning stocks. However, when testing the GRS statistics, both the CAPM and the four-factor model display p-values close to zero, which would indicate that both models should be rejected as they are not efficient.

Furthermore, the Sharpe ratio is measured as an extra performance check. In Table 7A, the Sharpe ratio increases from 2.923 for GSV1 to 3.404 for GSV3. In Table 7B, the Sharpe ratio increases zigzag from 2.792 for GSV1 to 3.471 for GSV10. Moreover, testing the statistical difference of the top and bottom portfolios (HMLGSV) results in a significant and positive test statistic of 3.364 (Table 7A) and 3.371 (Table 7B) under a significance level of 1%. This implies that high GSV ticker portfolios statistically outperform low GSV ticker portfolios. Therefore, an HML investing strategy is more profitable, implying one should go long in the high portfolio and short in the low portfolio.

In short, the high ticker GSV portfolio significantly differs from the low GSV portfolio after adjusting for risk. Based on the above results, it can be concluded that high ticker attention stocks outperform relative to low ticker attention stocks. Therefore, there is significant evidence to reject Hypothesis 2a that firms with low investor attention by ticker searches have higher risk-adjusted returns.

Table 7A: Single sort GSV ticker portfolio for CAPM & four-factor model (Terciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for GSV ticker portfolios constructed terciles. The terciles, GSV1 (Low), GSV2 (Medium), and GSV3 (High), are equally divided based on the mean standardized value of GSV (Mean GSV Ticker). Moreover, the High minus Low (HMLGSV) reflects the zero-investment strategy portfolio, which takes a long (short) position in the high (low) ranked firms in terms of their respective standardized value of GSV. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. Sharpe ratio is presented per individual portfolio, including Memmel's (2003) Z statistic to test the statistical difference for the HMLGSV portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

GSV Ticker Portfolio Alpha (No. of quantiles = 3) (CAPM)				
	GSV1	GSV2	GSV3	HMLGSV
Alpha	0.002**	0.002**	0.002***	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.520***	0.536***	0.549***	0.030**
	(0.07)	(0.07)	(0.07)	(0.01)
GRS	4.485**	5.900**	7.178***	6.263**
Sample (N)	363	363	363	363
R-squared	0.292	0.310	0.312	0.028
Adj R-squared	0.290	0.308	0.310	0.025
F	60.99***	61.66***	61.64***	6.12**
GSV Ticker Portfolio Alpha (No. of quantiles = 3) (4-factor model)				
	GSV1	GSV2	GSV3	HMLGSV
Alpha	0.002**	0.002**	0.002***	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.529***	0.549***	0.568***	0.038***
	(0.07)	(0.07)	(0.07)	(0.01)
SMB	0.230*	0.240*	0.286**	0.057**
	(0.13)	(0.13)	(0.13)	(0.02)
HML	0.044	0.090	0.072	0.030
	(0.12)	(0.11)	(0.11)	(0.02)
MOM	-0.000	0.030	0.043	0.043***
	(0.08)	(0.07)	(0.07)	(0.02)
GRS	4.861**	6.289**	7.467***	5.473**
Sharpe Ratio	2.923	3.194	3.404	2.834
SR test Z				3.364***
Sample (N)	363	363	363	363
R-squared	0.300	0.319	0.325	0.064
Adj R-squared	0.293	0.312	0.317	0.054
F	17.00***	17.62***	17.57***	6.22***
Mean GSV Ticker	-0.812	-0.055	0.867	.

Table 7B: Single sort GSV ticker portfolio for CAPM & four-factor model (Deciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for GSV ticker portfolios constructed deciles. The deciles, GSV1 (Low) up to GSV10 (High), are equally divided based on their mean standardized value of GSV (Mean GSV Ticker). Moreover, the High minus Low (HMLGSV) reflects the zero-investment strategy portfolio, which takes a long (short) position in the highest (lowest) ranked firms in terms of their respective standardized value of GSV. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the Sharpe ratio (SR) is presented per individual portfolio. 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

GSV Ticker Portfolio Alpha (No. of quantiles = 10) (CAPM)											
	GSV1	GSV2	GSV3	GSV4	GSV5	GSV6	GSV7	GSV8	GSV9	GSV10	HMLGSV
Alpha	0.001*	0.001**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002***	0.002***	0.002***	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.538***	0.529***	0.506***	0.505***	0.554***	0.538***	0.524***	0.523***	0.563***	0.571***	0.033*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.02)
GRS	3.797*	4.014**	4.024**	6.307**	5.453**	6.295**	4.702**	7.192***	7.294***	7.608***	6.386**
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.309	0.294	0.260	0.277	0.314	0.302	0.292	0.283	0.318	0.317	0.013
Adj R^2	0.307	0.292	0.258	0.275	0.312	0.300	0.290	0.281	0.316	0.315	0.010
F	68.44***	62.18***	52.88***	52.45***	64.33***	62.81***	59.53***	52.80***	61.82***	68.38***	3.81*
GSV Ticker Portfolio Alpha (No. of quantiles = 10) (4-factor model)											
	GSV1	GSV2	GSV3	GSV4	GSV5	GSV6	GSV7	GSV8	GSV9	GSV10	HMLGSV
Alpha	0.001*	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002***	0.002***	0.002***	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.550***	0.538***	0.516***	0.515***	0.565***	0.551***	0.544***	0.541***	0.580***	0.587***	0.037**
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.02)
SMB	0.218	0.259*	0.246*	0.170	0.248*	0.238*	0.290**	0.296**	0.273**	0.284**	0.066
	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.14)	(0.13)	(0.04)
HML	-0.003	0.068	0.049	0.102	0.107	0.078	0.088	0.089	0.095	0.015	0.018
	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.04)
MOM	0.003	-0.005	-0.004	0.035	0.021	0.029	0.060	0.039	0.049	0.014	0.011
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.03)
GRS	3.934**	4.540**	4.427**	6.589***	5.987**	6.634***	4.860**	7.603***	7.606***	7.880***	6.486**
SR	2.792	2.827	2.802	3.250	3.118	3.259	2.966	3.398	3.424	3.471	2.770
SR test Z											3.371***
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.316	0.305	0.269	0.283	0.324	0.311	0.306	0.296	0.330	0.328	0.022
Adj R^2	0.309	0.297	0.260	0.275	0.317	0.303	0.298	0.288	0.322	0.320	0.011
F	18.08***	17.75***	14.89***	15.49***	18.95***	17.47***	17.11***	15.72***	17.83***	18.30***	2.09*
Mean GSV Ticker	-1.218	-0.783	-0.558	-0.368	-0.164	0.049	0.280	0.534	0.832	1.405	.

5.2.2 Company Name Google Searches

Secondly, the results of company name Google searches will be reviewed in the single sort investor attention.

> ***H2b**: "Firms with low investor attention by company name searches have higher risk-adjusted returns than high investor attention firms."*

Tables 8A and 8B (in Appendix) show the GSV results of company name searches and their effect on portfolio returns in terciles and deciles. Table 8A shows average standardized values of -0.737 (GSV1), -0.049 (GSV2), and 0.788 (GSV3) for the respective low, medium, and high company name GSV portfolios. Table 8A shows positive and significant alphas for the low (GSV1), medium (GSV2), and high (GSV3) portfolios in both the CAPM and the four-factor model. The alpha for GSV1 is the most significant in the four-factor model. Again, the high minus low portfolio is added to the model to show a clear difference between both portfolios since the results are difficult to measure since all GSV portfolios outperform. HMLGSV (terciles) shows a negative and significant value which reveals that the low company name GSV portfolio (GSV1) outperforms the high company name GSV portfolio (GSV3). As the difference in portfolios regarding the terciles is difficult to interpret, Table 8B refers to the portfolio construction in deciles to show closer effects of GSV. Table 8B shows that the mean standardized values range from -1.119 for low attention (GSV1) to 1.306 for high attention (GSV10). Again, all GSV portfolios have positive and are significant alphas for both the CAPM and the four-factor model, as expected. GSV1, GSV2, and GSV4 are the most significant for the four-factor model, with an alpha of 0.2% under a significance level of 1%. In contrast, the CAPM only shows a strong significant alpha of 0.2% for GSV1 under a significance level of 1%. Moreover, the HMLGSV (deciles) shows a negative but insignificant value indicating no clear outperformance between GSV1 and GSV10. However, from Table 8A can be seen that low company name attention (GSV1) outperforms high company name attention (GSV3) when constructing heavier attention portfolios.

The following paragraph will briefly elaborate on the effects of the different risk factors. Table 8A and 8B show positive and strong significance (1% level of significance) for all portfolios' market risk premium of except for both tables' high minus low portfolio. For the SMB risk factor, Table 8A shows positive and significant values with medium attention (GSV2) as the most significant value under a 5% significance level. The values in Table 8B differ per portfolio for the SMB risk factor. All portfolios are significant except for GSV2, GSV9, and GSV11. The risk factor SMB has the most effect on the portfolios GSV4 up to GSV7 and GSV10. The risk factor HML does not have significant value in both Table 8A and Table 8B, which indicates that there are no value (book-to-market equity) differences between portfolios. There also seems no significant difference between winner and loser stocks as there is no significant value for the momentum risk factor there except for the high minus low portfolio (HMLGSV terciles). Thus, the high-rated ESG portfolio has more winners than losers in the past 12 months. However, when testing the GRS statistics, Tables 8A and 8B reveal that both the CAPM and the four-factor model display p-values close to zero, which would indicate that both models should be rejected as they are not efficient.

Finally, the Sharpe ratio is calculated for company name GSV to measure the outperformance of the portfolios. Firstly, Table 8A shows that low attention (GSV1) has the highest Sharpe ratio with a value of 3.362. The same can be seen in Table 8B, where GSV1 has the highest Sharpe ratio of 3.403. However, scrutinizing Table 8B in more depth shows that the outperformance differs per portfolio, whereas portfolio GSV10 (high) has a value of 3.058 relative to portfolio GSV5 (medium) which has a value of 2.930.

In Table 8A, the Sharpe ratio decreases from 3.362 for GSV1 to 3.042 for GSV3. In Table 7B, the Sharpe ratio decreases zigzag from 3.403 for GSV1 to 3.058 for GSV10. Moreover, testing the statistical difference of the top and bottom portfolios (HMLGSV) results in a significant test statistic of -1.633 under a significance level of 10% (Table 8A) and -1.685 under a significance level of 5% (Table 8B). This implies that low GSV company name portfolios statistically outperform high GSV company name portfolios. Therefore, a contrarian investing strategy is more profitable, implying one should go long in the low portfolio and short in the high portfolio (LMH portfolio).

In short, the lowest company name attention portfolio (GSV1) outperforms relative to the other portfolios. Based on the above results, it can be concluded that low company name attention stocks outperform relative to high company name attention stocks. Therefore, there is significant evidence to accept Hypothesis 2b.

5.2.3 Composite Google Searches

Finally, this section reviews the results of composite Google searches in the single sort approach for investor attention.

> ***H2c****: "Firms with low investor attention by composite searches have higher risk-adjusted returns than high investor attention firms."*

Tables 9A and 9B (in Appendix) show the composite GSV results by combining the ticker and company name searches and their portfolio returns in terciles and deciles. As high ticker GSV and low company name GSV portfolios outperformed, one would expect that effect of composite investor attention on portfolio returns will be ambiguous. Table 9A shows average standardized values of -0.592 (GSV1), -0.023 (GSV2), and 0.616 (GSV3) for the respective low, medium, and high company name GSV portfolios. Table 9A shows positive and significant alphas for the low (GSV1), medium (GSV2), and high (GSV3) portfolios in both the CAPM and the four-factor model. The high minus low portfolio shows no significant difference between the high and low portfolios as its value is zero and not significant. Therefore, Table 9B will be scrutinized to show the closer effects of overall investor attention on portfolio returns. The alphas for the CAPM and the four-factor model are all the same, positive and significant under a significance level of 5%. However, logically the high minus low portfolio (HMLGSV) is again neutral and not significant as the alphas for the low and high portfolio are the same.

Moreover, the market risk premium is positive and significant for all portfolios. Furthermore, the SMB risk factor is only not significant for GSV2, GSV3, and HMLGSV in Table 9B. The HML risk factor shows no significant values for any portfolios, meaning that the value (book-to-market equity) stocks have no impact on returns. Lastly, the momentum (MOM) risk factor is only significant for the high minus low (HMLGSV) portfolios in Table 9A and Table 9B. This indicates that there are more winners than losers in the high-rated ESG portfolio. However, again when testing the GRS statistics, Tables 9A and 9B reveal that both the CAPM and the four-factor model display p-values close to zero, which would indicate that both models should be rejected as they are not efficient.

In Table 9A, the Sharpe ratio increases from 3.102 for GSV1 to 3.277 for GSV3. In Table 9B, the Sharpe ratio increases zigzag from 2.901 for GSV1 to 3.239 for GSV10, with the medium portfolio GSV5 as the highest Sharpe ratio with a value of 3.402. Moreover, testing the statistical difference of the top and bottom portfolios (HMLGSV) results in a test statistic of 0.970 (Table 9A) and 1.204 (Table 9B) that are both not significant. This implies that the Sharpe ratios do not statistically differ from each other. Therefore, high composite GSV portfolios do not statistically outperform low composite GSV portfolios.

In short, the above results about the composite portfolio indicate that all GSV portfolios outperform the market, resulting in an ambiguous value to decide if low rather than high composite GSV portfolios outperform. Thus, high composite GSV portfolios do not statistically outperform low composite GSV portfolios. Therefore, there is enough evidence to reject Hypothesis 2c.

5.3 Double sorting: Sorted by ESG and investor attention

In the above sections, the single sort approach is used to measure the separate effects of ESG factors and investor attention on stock performance. After finding the separate effects, a double sorting approach is used to find each factor’s additional effect on the other. The objective is to find the driving force of both ESG and investor attention and its effect on returns. This will be done by applying a double sorting approach to the method. Therefore, the third general hypothesis stated below will be tested in this results section.

***H3**: "High-rated ESG firms and firms with low investor attention have the highest risk-adjusted returns relative to the other combinations."*

The double sorting approach is measured by sorting portfolios in terciles and finding the outperformance of each combination. There are nine sorted portfolios based on low, medium, and high ESG and investor attention. Again, the alphas of the CAPM and the four-factor model are calculated to evaluate each portfolio's performance. As stated in the hypothesis, the objective is to find the additional effect of GSV on ESG portfolios. To test the above hypothesis, investor attention is divided again into ticker, company name, and composite Google searches, resulting in the three hypotheses to test each separate effect. Therefore, the following sub-sections will review the results for ticker, company names, and composite searches showed respectively in tables 8, 9, and 10.

5.3.1 Double Sorting: ESG and Ticker Google Searches

Firstly, the results of ESG and ticker Google searches will be reviewed in the double sorting approach.

> ***H3a**: "High-rated ESG firms and firms with low investor attention by ticker searches have the highest risk-adjusted returns relative to the other combinations."*

Examining Table 10 gives the double sorting results for ESG and ticker GSV and its effect on stock portfolio returns. Both portfolios are sorted from low to high in each ESG and GSV combination possible. A low ESG (ESG1) and low ticker investor attention (GSV1) have a mean ESG value of 34.76 and a mean GSV value of -0.809. On the other hand, a high ESG (ESG3) and high ticker investor attention (GSV3) have a mean ESG value of 78.11 and a mean GSV value of 0.871.

Table 10 shows positive and significant alphas for the CAPM in all low and medium ESG portfolios irrespectively the GSV level. These portfolios are ESG1-GSV1 up to ESG2-GSV3. Moreover, the market risk premium factor of all portfolios is positive and significantly different from zero. Furthermore, the four-factor model is compared with the CAPM to study the differences. Besides the CAPM, the four-factor model even shows slightly significant alphas for two high ESG portfolios, namely high ESG and low GSV (ESG3-GSV1), as well as high ESG and high GSV (ESG3-GSV3). The high ESG and medium attention portfolio (ESG3-GSV2) is not statistically different from zero and therefore shows no outperformance.

As expected from the single sorted results, the alphas are the highest and most significant for the low ESG portfolios. Moreover, the low ESG and high ticker GSV portfolio (ESG1-GSV3) is the most significant. Therefore, it shows the highest outperformance relative to the other portfolios with an alpha of 0.3% under a 1% significance level. This is in line with the single sorted results as the low ESG portfolio, and the high ticker GSV portfolio had the highest alphas in the single sorting approach.

The following paragraph will elaborate briefly on the effects on the different risk factors of the four-factor model. As in the CAPM, the market risk premium is for all portfolios positive and significant. The market risk premium explains return movements in the market as all values are statistically different from zero. The SMB risk factor is the highest for the low ESG and high attention portfolio (ESG1-GSV3) with a value of 37.1%, indicating that firms low rated ESG firms with high ticker searches are small firms that outperform larger firms, which is in line with the theory of Fama and French (1993). The HML risk factor is for all portfolios not statistically different from zero, which implies that value firms do not have higher returns than growth regarding the book-to-market equity ratio. Lastly, the MOM factor is not significantly different from zero as well. This indicating that past winners did not outperform past losers over the last year in the double sorting ticker portfolios. However, when testing the GRS statistics, both the CAPM and the four-factor model display p-values close to zero, which would indicate that both models should be rejected as they are not efficient.

Again, the Sharpe ratio is calculated to evaluate the performance per portfolio as last check. The Sharpe ratio is the highest for the low ESG and high ticker GSV portfolio (ESG1-GSV3), with a value of 4.184. This result is in line with the outperformance evaluated by the CAPM and four-factor model asset pricing models. Moreover, the medium rated ESG and medium ticker GSV portfolio (ESG2-GSV2) has the second-highest Sharpe ratio with a value of 3.635. This result is unexpected since low-rated ESG portfolios tend to have a stronger effect on returns than the attention effect. However, it is a close call since another low ESG portfolio (ESG1-GSV2) shows almost a similar value of 3.540, indicating almost the same performance.

To conclude, the above results show that the low-rated ESG firms and high investor attention outperforms other portfolios in the double sorting method for ticker searches. These findings are in line with the results of the single sorting model for ESG and ticker GSV. Hence, Hypothesis 3a can be rejected.

Table 10: Double sort ESG-GSV ticker portfolio for CAPM & four-factor model (Terciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the double sorted approach for ESG and GSV ticker combined portfolios constructed terciles. The terciles for both factors, ESG1 (Low), ESG2 (Medium), and ESG3 (High) as well as GSV1 (Low), GSV2 (Medium), and GSV3 (High), are equally divided based on the mean ESG and standardized value of GSV (Mean GSV ticker). The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. The Sharpe ratio is presented per individual portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

ESG-GSV Ticker Portfolio Alpha (No. of quantiles = 3) (CAPM)									
	ESG1-GSV1	ESG1-GSV2	ESG1-GSV3	ESG2-GSV1	ESG2-GSV2	ESG2-GSV3	ESG3-GSV1	ESG3-GSV2	ESG3-GSV3
Alpha	0.002**	0.002***	0.003***	0.002**	0.002***	0.002**	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.495***	0.534***	0.515***	0.524***	0.521***	0.555***	0.543***	0.553***	0.570***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
GRS	6.573***	8.113***	12.963***	4.147**	8.741***	6.371**	2.332	2.010	2.733*
N	363	363	363	363	363	363	363	363	363
R^2	0.265	0.282	0.272	0.284	0.299	0.308	0.300	0.317	0.314
Adj R^2	0.263	0.280	0.270	0.282	0.298	0.306	0.298	0.315	0.312
F	50.31***	51.82***	48.15***	57.57***	63.07***	61.34***	73.11***	69.07***	70.67***

ESG-GSV Ticker Portfolio Alpha (No. of quantiles = 3) (4-factor model)									
	ESG1-GSV1	ESG1-GSV2	ESG1-GSV3	ESG2-GSV1	ESG2-GSV2	ESG2-GSV3	ESG3-GSV1	ESG3-GSV2	ESG3-GSV3
Alpha	0.002**	0.002***	0.003***	0.002**	0.002***	0.002**	0.001*	0.001	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.511***	0.556***	0.546***	0.534***	0.534***	0.575***	0.546***	0.555***	0.575***
	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
SMB	0.249*	0.352**	0.371***	0.200	0.218*	0.270**	0.228*	0.152	0.223
	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)
HML	0.007	0.057	0.018	0.038	0.104	0.122	0.076	0.111	0.091
	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)
MOM	0.023	0.044	0.078	0.009	0.038	0.074	-0.036	-0.001	-0.013
	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)
GRS	6.654***	8.450***	12.842***	4.364**	9.154***	6.550**	2.918*	2.404	3.241*
SR	3.289	3.540	4.184	2.848	3.635	3.274	2.429	2.355	2.549
N	363	363	363	363	363	363	363	363	363
R^2	0.275	0.300	0.295	0.290	0.308	0.321	0.309	0.323	0.322
Adj R^2	0.267	0.293	0.287	0.282	0.301	0.314	0.302	0.316	0.315
F	13.72***	15.27***	14.31***	16.15***	18.22***	18.32***	20.25***	19.50***	19.34***
Mean ESG	34.76	34.46	34.78	59.10	59.09	59.18	78.17	77.86	78.11
Mean GSV Ticker	-0.809	-0.058	0.855	-0.799	-0.030	0.873	-0.820	-0.070	0.871

5.3.2 Double Sorting: ESG and Company Name Google Searches

Secondly, this section reviews the results of ESG and company Google searches in the double sorting approach.

> ***H3b****: "High-rated ESG firms and firms with low investor attention by company name searches have the highest risk-adjusted returns relative to the other combinations."*

Table 11 (in Appendix) shows the CAPM and four-factor model results of the double sorting approach for ESG and company name searches for investor attention. Nine double sorted portfolios are constructed based on their low to high ESG rating and GSV. A low ESG (ESG1) and low company name GSV (GSV1) has a mean ESG value of 34.98 and a mean GSV value of -0.726. On the other hand, a high ESG (ESG3) and high company name GSV (GSV3) has a mean ESG value of 78.04 and a mean GSV value of 0.807.

Table 11 (in Appendix) reveals that the CAPM shows almost the same signs of alphas except for the high ESG and low attention portfolio (ESG3-GSV1) and the high ESG and medium attention portfolio (ESG3-GSV2). The latter show slightly more significant signs of alphas. The market risk premium is significantly different from zero for all according to the CAPM as they explain the returns by market movements positively.

Regarding the four-factor model, the strongest signs of alphas can be found in the low ESG portfolios. These are all the low ESG portfolios regardless of the level of attention by company name searches. The portfolios ESG1-GSV1, ESG1-GSV2, and ESG1-GSV3 all have statistically significant 0.2% alphas per month. Moreover, even the medium ESG rated and low attention portfolio (ESG2-GSV1) has the same alpha of 0.2% per month, which indicates that there seems no clear difference in outperformance for low rated ESG portfolios. However, the alpha of the ESG2-GSV1 portfolio could indicate that low attention puts more weight on returns. This finding is in line with the results of the single sorted approach for company name GSV. Next to the alphas, the different risk factors will be elaborated briefly. Similar to the CAPM, the four-factor model shows statistically significant and positive market risk premia for all portfolios. Moreover, the SMB risk factor is not statistically different from zero for two high-rated ESG portfolios, namely the portfolios with low and high attention (ESG3-GSV1 and ESG3-GSV3). The SMB risk factor shows the most significant results for all three low ESG-rated portfolios regardless of the attention effect. The portfolios (ESG1-GSV1, ESG1-GSV2, & ESG1-GSV3) show positive factors with values ranging from 0.322 to 0.315 per month under a 5% significance level. This indicates that small stocks show higher returns relative to big stocks within the low-rated ESG firms. The HML and MOM risk factors do not show statistically significant results, indicating that value stocks (high market-to-book ratio) and past winner stocks do not show higher returns in their portfolio. However, when testing the GRS statistics, both the CAPM and the four-factor model display p-values close to zero, which would indicate that both models should be rejected as they are not efficient.

Subsequently, the Sharpe ratio is determined to study the performance per portfolio more in-depth. The Sharpe ratio is the highest for the low ESG and low company name GSV portfolio (ESG1-GSV1) with a value of 3.819. The other Sharpe ratios decline monotonically among higher ESG portfolios and higher attention, indicating that low attention results in a higher Sharpe ratio for all ESG portfolios. Therefore, the high ESG and high attention portfolio (ESG3-GSV3) shows the lowest ratio with a value of 2.154. These results are aligned with the performance evaluated by the CAPM and four-factor model asset pricing models.

The above results show that the low-rated ESG firms and low investor attention outperforms other portfolios in the double sorting method for company name searches. These findings are in line with the single sorting model for ESG and company name GSV. Therefore, Hypothesis 3b can be rejected.

5.3.3 Double Sorting: ESG and Composite Google Searches

Lastly, this section reviews the results of ESG and composite Google searches in the double sorting approach.

> ***H3c**: "High-rated ESG firms and firms with low investor attention by composite searches have the highest risk-adjusted returns relative to the other combinations."*

Table 12 (in Appendix) shows the CAPM and four-factor model results of the double sorting approach for ESG and company name searches for investor attention. Nine double sorted portfolios are constructed based on their low to high ESG rating and GSV. A low ESG (ESG1) and low company name GSV (GSV1) has a mean ESG value of 34.76 and a mean GSV value of -0.594. On the other hand, a high ESG (ESG3) and high company name GSV (GSV3) has a mean ESG value of 78.03 and a mean GSV value of 0.602.

This section will briefly review Table 12 (in Appendix) as the single sort composite GSV shows ambiguous results for all GSV portfolios. Therefore, the composite GSV does not have a differentiating effect on the single sorted ESG portfolios. Thus, table 10 reveals that all low ESG (ESG1) and medium ESG (ESG2) portfolios outperform regardless of the level of GSV with an alpha of 0.2% under a 1% and 5% significance level. However, when testing the GRS statistics, both the CAPM and the four-factor model display p-values close to zero, which would indicate that both models should be rejected as they are not efficient.

Moreover, the Sharpe ratio is the highest for the low ESG, medium, and high portfolios (ESG1-GSV2 and ESG1-GSV3) with a value of 3.831 and 3.847, respectively.

Hence, findings show that low and middle ESG as well as low and middle composite investor attention portfolios outperform. Therefore, the double sorting approach shows that attention has more explanatory value on ESG portfolios' returns, which indicates that there is an additional effect of attention (and not moderating) beyond ESG on stock returns. Although, the latter finding is vital for this research, Hypotheses 3c should be rejected since the high ESG-rated portfolio does not outperform.

5.4 Panel regression

As explained in the methodology section, this thesis performs lagged panel regressions to evaluate investor attention's effect on the returns and vice versa per ESG portfolios for each individual stock. The first subsection elaborates on the optimal lag determination for the panel regression. Moreover, the second subsection examines the effect of investor attention on returns per ESG portfolio and thereby answers Hypothesis 4a. Subsequently, the third subsection analyzes the effect of returns on investor attention per ESG portfolio, thereby answering Hypothesis 4b.

5.4.1 Optimal lag determination

To determine the number of optimal lags for the panel regression, a general panel should first be run. This thesis chooses to run the first general panel regression with 6 lags, indicating a *p* variable of 6, to determine the optimal number of lags. This indicates that 6 weekly lags will be used to find the short-term explanatory effect of GSV on returns.

Table 13 shows the results of the general panel regression where *p* has a value of 6. To start with the first lag of GSV, it can be seen that GSV has a positive and significant value from the 2^{nd} to the 6^{th} lag of returns. It can be seen that the returns change with every added lag until the 5^{th} lag. This indicates that each lag has a partial effect on the next lag. The correlation between lags decreases, and it can be seen that the effect for lag 3 until lag 6 is more or less the same. For example, regarding the 6^{th} lag, if GSV increases with 1 in the previous period, returns increase with 3-basis points. Moreover, the second GSV lag shows a reversed effect on lag for returns (which is in line with prior research). The negative and significant value indicates that GSV decreases returns after two weeks by 3% to 2.7%. The third GSV lag does not show any significant effects for each lag of returns. However, in the fourth GSV lag, another negative and significant effect of GSV on returns can be seen. The fourth GSV lag's significant values indicate that GSV decreases returns after two weeks by 1.7% to 1.9%. The fifth and sixth GSV lag do not show significant effects for GSV on returns. Therefore, it can be concluded that GSV has significant explanatory value until the fourth lag. Hence, the next panel regressions for expected returns and GSV will be using four lags as the optimal number of lags. Moreover, the adjusted R-squared increases until the fourth lag and then remains the same after adding more lags. This indicates that adding more than four lags does not result in more explanatory power of additional lags. Furthermore, the control variables' effects also show the most significant effects on returns until the fourth lag. Therefore, the general panel regression indicates the optimal number of lags used in the expected returns, and GSV panel regressions should be four. As the general panel regression is only run to determine the optimal number of lags, the control variables' effects on returns will not be elaborated here. They will be studied in more depth for the expected returns and GSV panel regression.

Table 13: General panel regression

This table presents the general panel regression results to estimate the optimal number of lags over the sample period 2013-2019. The impact of the independent variable GSV composite and the vector of control variables on the lagged dependent variable predicted returns are examined in the general panel regression. The table shows the effect on each lag's returns, indicating each variable's weekly affecting value per lag. The table shows Yes or No for week-fixed effects. Moreover, the R-squared and the R-squared between can be found. R-squared measures the proportion of the variance in the dependent explained by the independent variables. R-squared consists of the R-squared within and R-squared between. R-squared between is the variance between panels. A low R-squared between indicates that the most variance in the model can be explained by the variance between the same firm's observations. The F-statistic (F) shows the fit of the model by testing equal group means. 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

	Panel Regression					
	pred_return	pred_return	pred_return	pred_return	pred_return	pred_return
L.GSV_Composite	0.004	0.026**	0.028**	0.031***	0.030***	0.030***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L2.GSV_Composite		-0.030***	-0.030***	-0.027**	-0.027**	-0.028**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L3.GSV_Composite			-0.005	0.003	0.002	-0.000
			(0.01)	(0.01)	(0.01)	(0.01)
L4.GSV_Composite				-0.017*	-0.018*	-0.019*
				(0.01)	(0.01)	(0.01)
L5.GSV_Composite					0.002	0.000
					(0.01)	(0.01)
L6.GSV_Composite						0.006
						(0.01)
L.SD	9.147***	8.647*	7.207	7.486	7.276	6.958
	(2.26)	(4.46)	(5.16)	(5.20)	(5.27)	(5.45)
L2.SD		-1.895	-2.880*	-2.242	-2.197	-2.293
		(2.07)	(1.63)	(1.72)	(1.62)	(1.50)
L3.SD			8.405	8.775	8.767	8.586
			(6.28)	(5.82)	(5.70)	(5.43)
L4.SD				-3.159***	-2.878***	-3.054***
				(0.84)	(0.87)	(0.90)
L5.SD					0.508	-0.039
					(1.11)	(0.89)
L6.SD						3.647
						(3.53)

L.MV	-0.414***	19.334***	20.474***	20.616***	20.577***	20.591***
	(0.04)	(1.59)	(1.65)	(1.67)	(1.67)	(1.68)
L2.MV		-19.890***	-26.166***	-26.877***	-26.839***	-26.869***
		(1.59)	(2.00)	(2.05)	(2.06)	(2.07)
L3.MV			5.203***	7.476***	7.458***	7.530***
			(0.44)	(0.66)	(0.69)	(0.71)
L4.MV				-1.720***	-1.420***	-1.418***
				(0.31)	(0.52)	(0.55)
L5.MV					-0.287	-0.386
					(0.26)	(0.51)
L6.MV						0.053
						(0.34)
L.TOBQ	-0.074***	-0.223	-0.252	-0.222	-0.181	-0.167
	(0.02)	(0.20)	(0.23)	(0.21)	(0.19)	(0.19)
L2.TOBQ		0.136	0.159	0.164	0.115	0.097
		(0.18)	(0.27)	(0.28)	(0.26)	(0.26)
L3.TOBQ			0.001	0.324***	0.336***	0.323***
			(0.08)	(0.11)	(0.12)	(0.12)
L4.TOBQ				-0.360**	-0.657***	-0.667***
				(0.17)	(0.24)	(0.24)
L5.TOBQ					0.299***	0.414***
					(0.08)	(0.11)
L6.TOBQ						-0.094
						(0.08)
L.Turnover	0.044**	0.020	0.028	0.020	0.018	0.022
	(0.02)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
L2.Turnover		0.004	0.010	0.008	0.003	0.001
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L3.Turnover			-0.039	-0.041	-0.052	-0.051
			(0.05)	(0.05)	(0.05)	(0.04)
L4.Turnover				0.025	-0.004	-0.001
				(0.02)	(0.02)	(0.02)
L5.Turnover					0.054***	0.045**
					(0.02)	(0.02)
L6.Turnover						-0.007
						(0.03)
LEV	-0.010***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	6.949***	9.809***	8.789***	8.955***	8.978***	8.737***
	(0.68)	(0.64)	(0.63)	(0.65)	(0.67)	(0.67)
Week-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample (N)	412817	412274	411747	411227	410712	410162
R-squared	0.157	0.185	0.187	0.188	0.188	0.188
R-squared between	0.002	0.000	0.000	0.000	0.000	0.000
F	130.96***	171.39***	180.95***	174.09***	173.45***	170.23***

5.4.2 Panel regression expected returns by ESG portfolio

After finding the optimal number of lags, where *p* is four, the first panel regression can be run. This panel regression examines the lagged effect of GSV on returns for all three ESG portfolios. Therefore, this subsection tests the hypothesis stated below.

***H4a**: "Investor attention has a significant effect on returns in high-rated ESG portfolios."*

Table 14 shows the results for the expected returns per ESG portfolio. The different ESG portfolios are constructed to find the lagged effect of investor attention per subsample. The ESG portfolios low (1), medium (2), and high (3) have average ratings of respectively 34.68, 59.17, and 78.00. For the low ESG portfolio, only the first lag of GSV has a significant effect. This implies that predicted returns increase by 6.6% when the standardized value of GSV increases by 1 after one week. Therefore, investor attention only explains the returns for one week in the low ESG portfolio. Secondly, the medium ESG portfolio will be studied. Results show that the first lag does not explain returns. However, the second, third and fourth GSV lag does explain returns due to its significant values. Table 14 shows first a negative effect of GSV on returns in lag 2 of -4.3%, then a positive effect in lag 3 of 3.4%, and then again a negative effect on returns in lag 4 of 3.1%. The high ESG portfolio results reveal that GSV does not explain returns significantly in any of the four lags.

Moreover, the control variables will be studied to evaluate their effects on returns per lag. The standard deviation (SD) only significantly explains returns after four weeks in the low ESG portfolio by a negative value of 2.536. For the medium ESG portfolio, returns are explained by SD after 1, 2, and 4 weeks due to their significant positive (13.296), negative (-5.536), and negative (-4.771) lags. Furthermore, the returns of the high ESG portfolio are positively (11.190), negatively (-4.363), and again positively (6.220), explained by lag 1, 2, and 3 for SD. Subsequently, Table 14 shows a significant effect of market value (MV) on returns in each of the four lags. The first and third lag show positive effects on returns, whereas the second and fourth lag explains returns negatively. Tobin's Q explains returns in the second positively and negatively in the third lag for the low ESG portfolio. There is no significant effect of Tobin's Q in the medium portfolio. Moreover, Tobin's Q explains returns negatively (-1.082) in the second lag and positively (0.873) in the third lag. Furthermore, turnover only explains returns significantly in the first, second, and third lag for the high ESG portfolio by -0.122, 0.119, and -0.074. Finally, leverage explains returns negatively for the medium ESG portfolio by 0.6% and for the high ESG portfolio by 17.8%. Thus overall, standard deviation and market value explain returns the most as control variables given their significance.

In short, the panel regression intends to examine the lagged effect of investor attention (GSV) on predicted returns. The lagged effect of investor attention gives closers insights into the weekly effects on returns. Earlier research shows that returns go up in the short run and are negatively affected in the long run as prices are inflated due to higher investor attention. The above results do not show a significant effect of investor attention on returns for high ESG portfolios in this paper. Therefore, Hypothesis 4a can be rejected.

Table 14: Panel regression expected returns by ESG portfolio

This table presents the general panel regression results to estimate the optimal number of lags over the sample period 2013-2019. The impact of the independent variable GSV composite and the vector of control variables on the lagged dependent variable predicted returns are examined in the general panel regression. The table shows the effect on each lag's returns, indicating each variable's weekly affecting value per lag. The table shows Yes or No for week-fixed effects. Moreover, the R-squared and the R-squared between can be found. R-squared measures the proportion of the variance in the dependent explained by the independent variables. R-squared consists of the R-squared within and R-squared between. R-squared between is the variance between panels. A low R-squared between indicates that the most variance in the model can be explained by the variance between the same firm's observations. The F-statistic (F) shows the fit of the model by testing equal group means. Furthermore, ESG shows the mean ESG rating per portfolio. 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

Panel Regression Expected Returns by ESG Portfolio			
	ESG1	ESG2	ESG3
	pred_return	pred_return	pred_return
L.GSV_Composite	0.066***	0.014	0.008
	(0.02)	(0.02)	(0.02)
L2.GSV_Composite	-0.016	-0.043**	-0.018
	(0.02)	(0.02)	(0.02)
L3.GSV_Composite	-0.010	0.034**	-0.014
	(0.02)	(0.02)	(0.02)
L4.GSV_Composite	-0.015	-0.031**	-0.010
	(0.02)	(0.02)	(0.02)
L.SD	2.512	13.296***	11.190***
	(9.22)	(2.49)	(2.64)
L2.SD	0.438	-5.536***	-4.363**
	(2.77)	(1.79)	(1.98)
L3.SD	13.147	2.880	6.220**
	(11.03)	(2.04)	(2.58)
L4.SD	-2.536**	-4.771***	-2.353
	(1.17)	(1.47)	(1.78)
L.MV	17.968***	22.595***	20.884***
	(3.16)	(1.32)	(1.50)
L2.MV	-24.361***	-29.754***	-26.153***
	(4.04)	(1.65)	(1.85)
L3.MV	8.181***	8.181***	5.652***
	(1.39)	(0.93)	(0.98)
L4.MV	-2.436***	-1.777***	-0.997*
	(0.68)	(0.50)	(0.56)
L.TOBQ	-0.290	0.310	0.497

	(0.19)	(0.23)	(0.41)
L2.TOBQ	0.231	-0.455	-1.082*
	(0.21)	(0.30)	(0.56)
L3.TOBQ	0.290**	0.199	0.873**
	(0.15)	(0.29)	(0.44)
L4.TOBQ	-0.369**	-0.090	-0.269
	(0.16)	(0.18)	(0.25)
L.Turnover	0.129	-0.008	-0.122***
	(0.08)	(0.03)	(0.04)
L2.Turnover	-0.055	0.016	0.119***
	(0.05)	(0.04)	(0.04)
L3.Turnover	-0.024	-0.019	-0.074**
	(0.09)	(0.04)	(0.04)
L4.Turnover	0.009	0.027	0.043
	(0.03)	(0.03)	(0.03)
LEV	-0.125	-0.006***	-0.178***
	(0.17)	(0.00)	(0.06)
Constant	11.260***	13.443***	11.111***
	(1.80)	(1.19)	(1.10)
Week Fixed Effects	Yes	Yes	Yes
Sharpe Ratio	22.759	20.163	15.568
Sample (N)	135677	138108	137442
R-squared	0.167	0.204	0.217
R-squared between	0.004	0.001	0.006
F	101.25***	100.60***	137.14***
ESG	34.680	59.168	78.002

5.4.3 Panel regression GSV by ESG portfolio

This panel regression examines the lagged effect of returns on investor attention (GSV) for all three ESG portfolios, which can be seen as a reversed regression. Therefore, this subsection tests the hypothesis stated below.

***H4b**: "Returns has a significant effect on investor attention in high-rated ESG portfolios."*

Table 15 shows the results for GSV per ESG portfolio. The ESG portfolios have the same average ESG rating as in Table 14. Results show that returns only explain GSV for the low ESG portfolio positively in lag 2 and lag 3 by 2%. All other results found in Table 15 show that there is almost no effect of the independent variable, expected returns, and the control variables on investor attention. Therefore, Hypothesis 4b can be rejected since returns do not significant affect attention in high-rated ESG portfolios.

Table 15: Panel regression GSV by ESG portfolio

This table presents the general panel regression results to estimate the optimal number of lags over the sample period 2013-2019. The effect of the independent variable predicted returns and the vector of control variables on the lagged dependent variable GSV composite are examined in the general panel regression. The table shows the effect on each lag's returns, indicating each variable's weekly affecting value per lag. The table shows Yes or No for week-fixed effects. Moreover, the R-squared and the R-squared between can be found. R-squared measures the proportion of the variance in the dependent explained by the independent variables. R-squared consists of the R-squared within and R-squared between. R-squared between is the variance between panels. A low R-squared between indicates that the most variance in the model can be explained by the variance between the same firm's observations. The F-statistic (F) shows the fit of the model by testing equal group means. Furthermore, ESG shows the mean ESG rating per portfolio. 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

	Panel Regression GSV by ESG Portfolio		
	ESG1	ESG2	ESG3
	GSV Composite	GSV Composite	GSV Composite
L.pred_return	0.001	-0.000	-0.001
	(0.00)	(0.00)	(0.00)
L2.pred_return	0.002***	0.001	-0.000
	(0.00)	(0.00)	(0.00)
L3.pred_return	0.002***	0.000	0.000
	(0.00)	(0.00)	(0.00)
L4.pred_return	0.000	0.001	-0.000
	(0.00)	(0.00)	(0.00)
L.SD	0.645**	1.681***	1.079***
	(0.31)	(0.35)	(0.38)
L2.SD	0.191	1.334***	0.513
	(0.29)	(0.34)	(0.36)
L3.SD	0.377	1.328***	1.223***
	(0.27)	(0.35)	(0.36)
L4.SD	-0.419	0.797**	0.618
	(0.26)	(0.37)	(0.38)
L.MV	0.193***	-0.037	0.171*
	(0.07)	(0.10)	(0.10)
L2.MV	-0.266***	0.069	-0.006
	(0.07)	(0.11)	(0.10)
L3.MV	0.132**	0.041	-0.125
	(0.06)	(0.11)	(0.09)
L4.MV	0.098	0.043	0.211**
	(0.06)	(0.11)	(0.10)
L.TOBQ	0.000	0.101***	0.022
	(0.01)	(0.03)	(0.03)
L2.TOBQ	0.020*	-0.016	-0.042
	(0.01)	(0.03)	(0.03)
L3.TOBQ	-0.009	0.004	0.050*
	(0.01)	(0.03)	(0.03)
L4.TOBQ	0.003	-0.045	-0.083***

	(0.01)	(0.03)	(0.03)
L.Turnover	0.046***	0.041***	0.061***
	(0.01)	(0.01)	(0.01)
L2.Turnover	0.019***	0.006	0.026***
	(0.01)	(0.01)	(0.01)
L3.Turnover	0.017**	0.004	0.003
	(0.01)	(0.01)	(0.01)
L4.Turnover	0.034***	0.023***	0.013
	(0.01)	(0.01)	(0.01)
LEV	0.067	0.015***	0.007
	(0.12)	(0.00)	(0.04)
Constant	-3.502***	-2.675***	-5.201***
	(0.85)	(1.02)	(1.04)
Week Fixed Effects	Yes	Yes	Yes
Sharpe Ratio	22.759	20.163	15.568
Sample (N)	133947	136352	135710
R-squared	0.083	0.110	0.126
R-squared between	0.012	0.026	0.028
F	11.66***	16.20***	13.38***
ESG	34.680	59.168	78.002

5.5 Vector Autoregression (VAR) model and Granger causality

This section examines how the VAR model forms the basis for causality between variables and how Granger causality tests answer the hypothesis based on the VAR model.

The previous section examined the separate effects of GSV on returns and vice versa. This section studies both variables' combined effect for both expected returns and GSV as dependent variables by performing a vector autoregression (VAR) model. Therefore, the fifth sub-hypotheses stated below will be tested in this results section.

***H5a**: "Investor attention Granger causes returns in high-rated ESG portfolios."*

***H5b**: "Returns Granger cause investor attention in high-rated ESG portfolios."*

The first step of the VAR model is determining the optimal lag length. This will be done by reviewing the information criteria tested in Table 16. The below selection order criteria table shows the results from the first-, second-, third-, fourth-, fifth-, and sixth-order panel VAR models using the first six lags of the endogenous variables as instruments. When minimizing the moment and model selection criteria (MMSC), the second-order panel VAR (MBIC and MHQIC) and the sixth-order panel VAR

(MAIC) have the smallest values. Therefore, they are the preferred models based on the three model-selection criteria by Andrews and Lu (2001).

A decision should be made about the selected optimal number of lags based on the information criteria and further theory. Based on the beneath table, the information criteria suggest 2 or 6 weeks as optimal lags. Two or six weeks are not a logical time unit in accounting terms. Therefore, the VAR model's optimal lags will be 4 weeks as this number of lags falls in between the second and sixth lags, which the information criteria results show for the minimizing values per MMSC. Moreover, four lags, which is a month, seem to be a logical time unit in accounting terms as stock prices are reported in months, quarters, and years. Hence, four is the optimal lag length for the VAR model.

Table 16: Lag-order selection VAR

This table presents the selection order criteria' results to determine the optimal number of lags for the VAR model. Panel VAR analysis is predicated upon choosing the optimal lag order in both panel VAR specification and moment condition. Table 16 reports the overall coefficient of determination (CD) per lag (which captures the proportion of variation explained by the panel VAR model), Hansen's (1982) J statistic and corresponding p-value, and the different moment and model selection criteria (MMSC) developed by Andrews and Lu (2001) based on the J statistic, namely MBIC, MAIC, and MHQIC. Table 14 shows the least restrictive panel VAR model's estimation sample, that is, with the highest lag order used, for all models that the program would fit. The VAR model's optimal lag for is based on the minimalized value per MMSC, which is indicated by *.

Lags	CD	J	J p-value	MBIC	MAIC	MHQIC
1	0.342	678.367	0.000	368.897	630.367	555.640
2	-0.092	63.962	0.000	-193.930*	23.962	-38.311*
3	0.018	64.174	0.000	-142.139	32.174	-17.644
4	-0.755	39.777	0.000	-114.958	15.777	-21.587
5	-0.987	23.489	0.003	-79.667	7.489	-17.419
6	-3.924	7.321	0.120	-44.258	-0.679*	-13.134

The vector autoregression model by ESG portfolios can be found in Table 17. In the first column, the total of all ESG portfolios is illustrated to measure the effect over the whole sample. The total of the ESG portfolios has an average ESG score of 57.266. Moreover, the low, medium, and high ESG portfolios have average ESG ratings of 34.680 (low ESG), 59.168 (medium ESG), and 78.002 (high ESG), which are similar to the panel regressions in section 4.4. Table 17 shows the results for both expected returns and investor attention (GSV) as dependent variable.

The first part of the results studies the VAR with expected returns as dependent variable. Over the whole ESG sample, the independent variable, expected returns, explains the dependent variable returns negatively by 5.5% in lag 1 and positively by 1.4% in lag 4. Moreover, GSV negatively explains returns by significant values of 4% in lag 2 and 4.1% in lag 4. Furthermore, the control variables Tobin's q, turnover, and leverage impact returns significantly.

For the low ESG portfolio, the independent variable, expected returns, only explains the dependent variable returns negatively by 4.5% in lag 1 and positively by 2% in lag 4. Moreover, GSV does not explain returns significantly for any lag for the low ESG portfolio. Furthermore, the control variables: standard deviation, Tobin's Q, and turnover, significantly impact returns.

For the medium ESG portfolio, the independent variable, expected returns, has a negative impact of 6.5% in lag 1 and a negative impact of 2.4% in lag 3. Moreover, GSV negatively explains returns by a significant value of -10.7% and -9.9% in the second and fourth lag. Only Tobin's Q significantly impacts returns for the medium ESG portfolio.

For the high ESG portfolio, the independent variable, expected returns, significantly explains returns in all four lags. The first lag has a negative impact of 6.8%, followed by a positive impact of 0.9% in the second lag. Again a negative effect of 2.5% is found in the third lag, whereas the fourth lag shows a positive impact of 1.1%. Moreover, GSV only explains returns in the first lag positively by 6.2%. Here, Tobin's Q and turnover significantly negatively impact the dependent variable expected returns for the high ESG portfolio.

Subsequently, the VAR model with GSV as dependent variable will be scrutinized to find the jointly determined effect of lagged returns and lagged attention on overall investor attention. Over the whole ESG sample, expected returns significantly explain GSV after two weeks (lag 2) by a positive 0.1%. Moreover, all lags for GSV significantly explain the dependent variable GSV positively. This indicates that each added GSV lag has an additional effect that explains investor attention. The variables standard deviation, Tobin's Q, turnover, and leverage significantly affect the dependent variable GSV.

For the low ESG portfolios, expected returns only significantly explain GSV negatively after a month (lag 4) by 0.1%. Moreover, all lags for GSV significantly explain the dependent variable GSV positively. The variables standard deviation, market value, turnover, and leverage significantly affect the dependent variable GSV.

For the medium ESG portfolio, only in the second lag for expected returns, a significant effect of 0.2% can be found. Moreover, again all four GSV lags show a strong significant and positive impact on the dependent variable GSV. Here the controls: standard deviation and leverage significantly affect the dependent variable GSV.

Finally, for the high ESG portfolio, Table 17 shows no significant results for the effect of expected returns on the dependent variable GSV. However, lagged GSV again shows significant positive results for all four lags with its impact on the dependent variable investor attention. Here only market value impacts the dependent variable GSV as control. To conclude, returns increase after one week for high-rated ESG stocks, whereafter returns decrease after two and four weeks for medium-rated ESG stocks. These findings are in line with the attention-grabbing hypothesis of Blitz et al. (2020).

Table 17: Vector Autoregression by ESG Portfolio

This table presents the vector autoregression results per ESG portfolio over the sample period 2013-2019. The basic principle of the VAR is that there is no dependent or independent variable which indicates that an independent variable has the same explanatory value as a dependent variable. Therefore, the VAR model accounts for all variables to be jointly determined. This table measures if investor attention explains returns for a different level of ESG portfolios, and at the same time, if returns within the same ESG portfolios explain investor attention. Each variable in the VAR model is expressed as a function of its own lags while also expressed by all lags of the other variables in the model. The VAR model is characterized by the fact that every equation has exactly the same set of explanatory variables. The VAR model estimation is simple as it applies ordinary least squares (OLS) to each equation at one time. The table reveals the effect on each lag's returns, indicating each variable's weekly affecting value of per lag. Important to note, the indicator mlag is the max number of lags in the VAR. Moreover, tmin and tmax are the beginning and end of the sample period. N is the number of observations, and n is the number of firms in the VAR. Moreover, ESG shows the mean ESG rating per portfolio. 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

Vector Autoregression by ESG Portfolio				
	Whole sample	ESG1	ESG2	ESG3
	pred_return	pred_return	pred_return	pred_return
pred_return				
L.pred_return	-0.055***	-0.045***	-0.065***	-0.068***
	(0.00)	(0.01)	(0.01)	(0.01)
L2.pred_return	0.001	-0.004	-0.008	0.009*
	(0.00)	(0.00)	(0.01)	(0.01)
L3.pred_return	-0.007	0.011	-0.024***	-0.025***
	(0.01)	(0.01)	(0.01)	(0.00)
L4.pred_return	0.014***	0.020***	0.002	0.011**
	(0.00)	(0.00)	(0.01)	(0.00)
L.GSV_Composite	0.013	0.029	-0.082	0.062**
	(0.02)	(0.03)	(0.07)	(0.03)
L2.GSV_Composite	-0.040***	-0.017	-0.107***	-0.026
	(0.01)	(0.02)	(0.04)	(0.02)
L3.GSV_Composite	-0.018	-0.015	-0.041	-0.025
	(0.01)	(0.02)	(0.04)	(0.02)
L4.GSV_Composite	-0.041***	-0.025	-0.099**	-0.027
	(0.01)	(0.02)	(0.04)	(0.02)
SD	32.147	62.532*	-7.497	10.624
	(20.12)	(33.94)	(5.66)	(12.88)
MV	1.055	0.131	3.482	0.305
	(0.80)	(0.33)	(2.92)	(0.26)
TOBQ	0.511***	0.194***	3.222**	-0.620***

	(0.14)	(0.06)	(1.61)	(0.23)
Turnover	-0.457**	-0.471*	0.601	-1.105**
	(0.21)	(0.28)	(0.49)	(0.53)
LEV	-0.015**	-0.192	-0.005	0.028
	(0.01)	(0.66)	(0.01)	(0.20)
GSV_Composite				
L.pred_return	0.000	0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
L2.pred_return	0.001**	0.000	0.002**	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
L3.pred_return	0.000	0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
L4.pred_return	-0.000	-0.001**	0.001	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
L.GSV_Composite	0.305***	0.270***	0.309***	0.340***
	(0.00)	(0.00)	(0.01)	(0.00)
L2.GSV_Composite	0.148***	0.143***	0.155***	0.144***
	(0.00)	(0.00)	(0.01)	(0.00)
L3.GSV_Composite	0.116***	0.120***	0.112***	0.112***
	(0.00)	(0.00)	(0.01)	(0.00)
L4.GSV_Composite	0.121***	0.119***	0.126***	0.116***
	(0.00)	(0.00)	(0.01)	(0.00)
SD	1.504***	1.970***	1.633**	2.607
	(0.52)	(0.62)	(0.78)	(2.09)
MV	-0.012	0.280***	-0.130	0.179***
	(0.14)	(0.05)	(0.46)	(0.05)
TOBQ	-0.036*	0.003	-0.254	0.019
	(0.02)	(0.01)	(0.22)	(0.04)
Turnover	0.119***	0.108***	0.106	0.132
	(0.02)	(0.02)	(0.07)	(0.09)
LEV	0.007***	0.471***	0.006***	0.048
	(0.00)	(0.14)	(0.00)	(0.03)
Q	0.00	0.00	0.00	0.00
J	0.00	0.00	0.00	0.00
mlag	4	4	4	4
tmin	2013w50	2013w50	2013w50	2013w50
tmax	2019w51	2019w51	2019w51	2019w51
N	406284	134289	136419	135576
n	1308	633	807	629
ESG	57.266	34.680	59.168	78.002

After examining the VAR model results, Granger causality tests will be performed to determine the causality of investor attention and returns. First, a Granger causality test will be performed for all ESG portfolios together, indicating the whole sample. Subsequently, the Granger causality in all three low, medium, and high ESG portfolios are tested.

Before analyzing the Granger causality tests per ESG-rating level, the Granger causality of investor attention and returns will be examined for all ESG portfolios, thus over the whole sample. Table 18 shows the result of this test for the whole sample. The Granger causality test states a null hypothesis that investor attention does not "Granger-cause" returns for all ESG portfolios. Since there is a significant probability value of 0.000, this test's null hypothesis can be rejected. This reveals that returns are strongly explained by investor attention when performing a Granger causality test over the whole sample, thus for all ESG portfolios.

Table 18: Granger causality for all ESG portfolios (whole sample)

This table presents the results of the Granger causality test of GSV composite and predicted returns for all ESG portfolios (whole sample). The Chi-sq shows how well the statistical model fits the data set. The Prob. value presents the probability value of the significance level.

Vector Autoregression by ESG Portfolio (Granger) (Whole sample))

Dep. Variable	Excluded	Chi-sq	df	Prob. value
pred_return	GSV_Composite	23.668	4	0.000***
	ALL	23.668	4	0.000***
GSV_Composite	pred_return	7.221	4	0.125
	ALL	7.221	4	0.125

Subsequently, Granger causality tests will be performed per level of ESG portfolios.

Firstly, the Granger causality for the low ESG portfolio will be examined. Table 19 shows the Granger causality of investor attention and returns for the low ESG portfolio. The Granger causality test states a null hypothesis that investor attention does not "Granger-cause" returns for low ESG portfolios. The results reveal no Granger causality for both variables in the low ESG portfolio as there is no significant value to reject the null hypothesis of this test. To conclude, this reveals that the returns of low-rated ESG stocks are not explained by higher investor attention.

Table 19: Granger causality for low ESG portfolios

This table presents the results of the Granger causality test of GSV composite and predicted returns for the low ESG (ESG1) portfolio. The Chi-sq shows how well the statistical model fits the data set. The Prob. value presents the probability value of the significance level.

Vector Autoregression by ESG Portfolio (Granger) (ESG_q==1))

Dep. Variable	Excluded	Chi-sq	df	Prob. value
pred_return	GSV_Composite	4.964	4	0.291
	ALL	4.964	4	0.291
GSV_Composite	pred_return	4.632	4	0.327
	ALL	4.632	4	0.327

Secondly, the Granger causality for the medium ESG portfolios will be examined. Table 20 shows the Granger causality of investor attention and returns for the medium ESG portfolio. The Granger causality test states a null hypothesis that investor attention does not “Granger-cause” returns for medium ESG portfolios. The results show a significant probability value for GSV of 0.011. Therefore, this test’s null hypothesis can be rejected, which implies that investor attention “Granger causes” expected returns in the medium ESG portfolio. To conclude, this indicates that the returns of medium-rated ESG stocks are explained by higher investor attention.

Table 20: Granger causality for medium ESG portfolios

This table presents the results of the Granger causality test of GSV composite and predicted returns for the medium ESG (ESG2) portfolio. The Chi-sq shows how well the statistical model fits the data set. The Prob. value presents the probability value of the significance level.

Vector Autoregression by ESG Portfolio (Granger) (ESG_q==2))

Dep. Variable	Excluded	Chi-sq	df	Prob. value
pred_return	GSV_Composite	13.126	4	0.011**
	ALL	13.126	4	0.011**
GSV_Composite	pred_return	4.773	4	0.311
	ALL	4.773	4	0.311

Lastly, the Granger causality for the high ESG portfolio will be examined. The results for the high ESG portfolio are found in Table 21. The Granger causality test states a null hypothesis that investor attention does not “Granger-cause” returns for high ESG portfolios. The stated null hypothesis of this test can be rejected due to the significant probability value of 0.012. To conclude, this reveals that higher investor attention explains high-rated ESG stocks’ returns, whereby attention is dominant for returns.

Table 21: Granger causality for high ESG portfolios

This table presents the results of the Granger causality test of GSV composite and predicted returns for the high ESG (ESG3) portfolio. The Chi-sq shows how well the statistical model fits the data set. The Prob. value presents the probability value of the significance level.

Vector Autoregression by ESG Portfolio (Granger) (ESG_q==3))

Dep. Variable	Excluded	Chi-sq	df	Prob. value
pred_return	GSV_Composite	12.831	4	0.012**
	ALL	12.831	4	0.012**
GSV_Composite	pred_return	1.414	4	0.842
	ALL	1.414	4	0.842

After performing the VAR model and scrutinizing the Granger causality tests per ESG portfolios, we can conclude by answering Hypothesis 5a and Hypothesis 5b.

From the VAR model, it can be concluded that there runs causality from investor attention to returns in the medium- and high-rated ESG portfolios and not in low-rated ESG portfolios. Moreover, there runs causality from returns to investor attention in the low and medium ESG portfolios but not in the high ESG portfolios. The Granger causality tests show that investor attention Granger causes returns in the medium- and high-rated ESG portfolios but not in the low-rated ESG portfolio.

Based on the above findings, Hypothesis 5a, which states that investor attention Granger causes returns in high-rated ESG portfolios, can be accepted. However, Hypothesis 5b, which states that returns Granger cause investor attention in high-rated ESG portfolios, should be rejected.

6 DISCUSSION

This thesis examines the relation of ESG-rated firms, investor attention by Google searches, and financial stock performance. Intention of this specific chapter is to shed light on the limitations of this research before interpreting the final results and declaring concluding remarks in Chapter 7. Moreover, additional research is recommended in this discussion Chapter.

Firstly, the main limitation of this research is the frequency of the data. This paper is restricted to the ESG scores of the ASSET4 database. Effort has been executed to get access to monthly ESG scores from the databases Sustainalytics and CSRHub. However, the databases were not available for academic research within the financial resources of this thesis. Therefore, the database ASSET4 is used, which provides yearly ESG scores. Hence, the main limitation of this research is that ESG data is available every year. In contrast, investor attention data measured by Google searches is available weekly via Google Trends. As a result, ESG portfolios can only be rebalanced once a year, while investor attention portfolios can be rebalanced every month. The disparity between the frequency of the data indicates the double sorting approach’s results should be interpreted with carefulness. Focus of this thesis is on the ASSET4 database with yearly ESG scores. For this reason, this research shows the effect of investor attention per level of ESG score sorted on low, medium, and high levels. Still, monthly ESG would have been much more valuable since the causal effect of ESG and investor attention could be examined more accurately. This research intends to measure the short-term effects of investor attention on the stock returns of ESG-rated firms. Hence, when databases with monthly ESG scores are available, additional research with monthly scores would be recommended to obtain stronger results.

Moreover, the ESG database ASSET4 has two other limitations. Firstly, Halbritter and Dorfleitner (2015) identify that firms’ ESG ratings differ per ESG rating agency. Therefore, this thesis’s results should not be considered conclusive as it depends on the ESG scores from the ASSET4 database. Future research could control for this by taking several ESG rating databases into account. Secondly, the MSCI World Index is used as reference to obtain an acceptable global stock market data sample with high market value firms. As the ASSET4 database is limited to 7200 global companies, many companies within the MSCI World Index should be covered. However, ASSET4 could have missed essential companies due to not collecting the right ESG criteria to provide an ESG-rating for a company in the desired global data sample. Therefore, future research could use an ESG database with more covered companies that better fit the MSCI World Index.

The limitation of the Google search database, which measures investor attention, is related to using a global data sample in this research. Asian investors use Baidu as a search engine instead of Google. As a result, Google searches for Asian stocks will not capture the total investor attention of the Asian firms. Moreover, ticker code searches should be reviewed with caution as Asian firms use a digit ticker code. This might lead to inaccurate investor attention data for ticker searches. Therefore, this thesis controls for both ticker searches as well as company name searches. Based on the above limitations, the Google search investor attention results in this research should still be carefully reviewed.

The last important limitation of this thesis is that it does not take bid-ask spreads and, therefore, transaction costs into account. The risk-adjusted returns obtained in this research do not incorporate transaction costs. Therefore, it could be the case that when incorporating transaction costs into the model that the results would not be significant anymore after rebalancing. Hence, concluding remarks on this thesis should be carefully considered. Additional research that takes transaction costs into account is recommended to obtain more accurate results.

7 CONCLUSION

This thesis empirically researches the effect of ESG-rated firms and investor attention on financial stock returns. The MSCI World Index is used as reference to obtain global stock market data for high market value firms over the period 2013 to 2019. This paper contributes to existing literature by expanding prior research on ESG and attention and its relation to financial performance. Prior research explains the separate effects of ESG and investor attention on stock returns. However, it does not touch upon the combined effect and the causality of both variables. Moreover, this thesis contributes to existing literature by using Google searches as measure for investor attention, whereby it specifically examines the attention for ticker code, company name, and composite searches.

This thesis is structured from simple to more extensive analyses to examine the research question: *"Does high investor attention influence the effect ESG has on stock returns?"*

To answer the above research question, the hypotheses are also structured from simple to the most extensive analyses. Firstly, the CAPM and the Carhart (1997) four-factor model are performed in single and double sorting approaches to determine both variables' separate and combined effects on returns. Moreover, more robust analyses: panel regressions, vector autoregression models, and Granger causality tests are performed to obtain more nuanced answers to the research question. The hypotheses per model present the following findings.

Hypothesis 1: "High-rated ESG firms have higher risk-adjusted returns than low-rated ESG firms." is rejected as low ESG-rate firms outperform high ESG-rated firms for both CAPM and the Carhart four-factor model in the single sort ESG approach.

Moreover, Hypothesis 2 is divided into ticker code, company name, and composite Google searches to determine the effect of investor attention on stock returns:

> Hypothesis 2a: "Firms with low investor attention by ticker searches have higher risk-adjusted returns than high investor attention firms." is rejected as high ticker attention stocks outperform.
>
> Hypothesis 2b: "Firms with low investor attention by company name searches have higher risk-adjusted returns than high investor attention firms." is accepted as low company name investor attention outperforms.
>
> Hypothesis 2c: "Firms with low investor attention by composite searches have higher risk-adjusted returns than high investor attention firms." may be rejected since all composite attention portfolios outperform.

Hence, we may reject Hypothesis 2: "Firms with low investor attention have higher risk-adjusted returns than high investor attention firms." since high attention does not outperform the single sorting approach for the overall investor attention.

Accordingly, Hypothesis 3 is divided as well into ticker code, company name, and composite Google searches to determine the combined effect of ESG and investor attention on stock returns:

> Hypothesis 3a: "High-rated ESG firms and firms with low investor attention by ticker searches have the highest risk-adjusted returns relative to the other combinations." may be rejected since the low ESG and high ticker investor attention portfolios outperform.
> Hypothesis 3b: "High-rated ESG firms and firms with low investor attention by company name searches have the highest risk-adjusted returns relative to the other combinations." may be rejected as the low ESG and low company name investor attention portfolios outperform.
> Hypothesis 3c: "High-rated ESG firms and firms with low investor attention by composite searches have the highest risk-adjusted returns relative to the other combinations." may be rejected since low and middle ESG as well as low and middle composite investor attention portfolios outperform.

Hence, we may reject Hypothesis 3: "High-rated ESG firms and firms with low investor attention have the highest risk-adjusted returns relative to the other combinations." since high ESG and low attention do not outperform the double sorting approach. Although Hypothesis 3 is rejected, an additional effect of attention beyond ESG is found in the results.

Furthermore, the results are tested for robustness in multivariate analyses to obtain more accurate results to answer the research question. Firstly, the individual effects of investor attention per firm are tested in the fourth hypothesis. There are significant effects of attention and returns found in the low and middle ESG-rated portfolios, but not in the high ESG-rated portfolios, which is in line with the lagged panel regressions results. Hence, we may reject both Hypothesis 4a: "Investor attention has a significant effect on the returns in high-rated ESG portfolios." as well as Hypothesis 4b: "Returns has a significant effect on investor attention in high-rated ESG portfolios" since there is no significant effect of attention on returns and vice versa of returns on investor attention found in high-rated ESG portfolios.

For the final extensive analyses, the vector autoregression (VAR) model and corresponding Granger causality tests are performed. These analyses show that there runs causality from investor attention to returns in the medium and high ESG portfolios and not in low ESG portfolios. Accordingly, the Granger causality tests show that investor attention Granger causes returns in the medium and high portfolios but not in the low ESG portfolio. Hence, we may accept Hypothesis 5a: "Investor attention Granger causes returns in high ESG portfolios". However, Hypothesis 5b: "Returns Granger cause investor attention in high-rated ESG portfolios" is rejected since there runs causality from returns to investor attention in the low and medium ESG portfolios but not in the high ESG portfolios.

Based on above findings, this paper concludes that the stock returns of low ESG-rated portfolios outperform relative to high ESG-rated portfolios. This finding is in line with prior ESG literature but may deviate from other ESG research depending on their ESG rating agency and/or financial markets used. The most recent research by Pastor et al. (2020) confirms this finding by showing that low ESG-rated stocks have higher alphas. Nevertheless, investors still hold high-rated ESG stocks, despite the negative returns due to strong ESG preference, according to Pastor et al. (2020). Moreover, from extensive analyses, we may conclude that the overall investor attention has an additional effect beyond the ESG-rating of firms on stock returns.

To conclude, from prior research, general investor attention expects a temporary effect of attention on returns due to the attention-grabbing hypothesis (Da et al., 2011). This paper finds that the additional effect of investor attention deviates per ESG-rated portfolio, showing the strongest results for medium and high ESG-rated portfolios, which is different from prior research. This paper's findings interpret that corporate socially responsibility (CSR) is not crucial within investment decisions to earn higher alpha. In fact, investing in low ESG-rated firms leads to higher alpha, consistent with Pastor et al. (2020). Moreover, firms with high attention have more effect on returns when integrating ESG factors into investment decisions, especially for medium and high ESG scores. Thus, above study reveals that ESG investing is not yet the new gold when chasing returns.

Table 22: Summary table hypotheses

Hypothesis	**Accept / Reject**
***Hypothesis* 1:** *"High-rated ESG firms have higher risk-adjusted returns than low-rated ESG firms."*	Reject
***Hypothesis 2**:* *"Firms with low investor attention have higher risk-adjusted returns than high investor attention firms."*	Reject
***Hypothesis 2a**:* *"Firms with low investor attention by ticker searches have higher risk-adjusted returns than high investor attention firms."*	Reject

***Hypothesis 2b**:* *"Firms with low investor attention by company name searches have higher risk-adjusted returns than high investor attention firms."*	Accept
***Hypothesis 2c**:* *"Firms with low investor attention by composite searches have higher risk-adjusted returns than high investor attention firms."*	Reject
***Hypothesis 3**:* *"High-rated ESG firms and firms with low investor attention have the highest risk-adjusted returns relative to the other combinations."*	Reject
***Hypothesis 3a**:* *"High-rated ESG firms and firms with low investor attention by ticker searches have the highest risk-adjusted returns relative to the other combinations."*	Reject
***Hypothesis 3b**:* *"High-rated ESG firms and firms with low investor attention by company name searches have the highest risk-adjusted returns relative to the other combinations."*	Reject
***Hypothesis 3c**:* *"High-rated ESG firms and firms with low investor attention by composite searches have the highest risk-adjusted returns relative to the other combinations."*	Reject
***Hypothesis 4a**:* *"Investor attention has a significant effect on returns in high-rated ESG portfolios."*	Reject
***Hypothesis 4b**:* *"Returns has a significant effect on investor attention in high-rated ESG portfolios."*	Reject
***Hypothesis 5a**:* *"Investor attention Granger causes returns in high-rated ESG portfolios."*	Accept
***Hypothesis 5b**:* *"Returns Granger cause investor attention in high-rated ESG portfolios."*	Reject

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APPENDIX

Table 8A: Single sort GSV company name portfolio for CAPM & four-factor model (Terciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for GSV company name portfolios constructed terciles. The terciles, GSV1 (Low), GSV2 (Medium), and GSV3 (High), are equally divided based on the mean standardized value of GSV (Mean GSV Company Name). Moreover, the High minus Low (HMLGSV) reflects the zero-investment strategy portfolio, which takes a long (short) position in the high (low) ranked firms in terms of their respective standardized value of GSV. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. Sharpe ratio is presented per individual portfolio, including Memmel's (2003) Z statistic to test the statistical difference for the HMLGSV portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

GSV Company Name Portfolio Alpha (No. of quantiles = 3) (CAPM)				
	GSV1	GSV2	GSV3	HMLGSV
Alpha	0.002**	0.002**	0.002**	-0.000*
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.537***	0.530***	0.541***	0.004
	(0.07)	(0.07)	(0.07)	(0.01)
GRS	6.921***	5.637**	5.040**	3.024*
Sample (N)	363	363	363	363
R-squared	0.304	0.298	0.313	0.000
Adj R-squared	0.302	0.296	0.311	-0.002
F	63.11***	61.25***	61.96***	0.11
GSV Company Name Portfolio Alpha (No. of quantiles = 3) (4-factor model)				
	GSV1	GSV2	GSV3	HMLGSV
Alpha	0.002***	0.002**	0.002**	-0.000**
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.546***	0.542***	0.560***	0.014
	(0.07)	(0.07)	(0.07)	(0.01)
SMB	0.236*	0.269**	0.255*	0.019
	(0.14)	(0.13)	(0.13)	(0.03)
HML	0.047	0.093	0.062	0.016
	(0.11)	(0.11)	(0.12)	(0.03)
MOM	-0.004	0.014	0.053	0.058***
	(0.07)	(0.07)	(0.07)	(0.02)
GRS	7.455***	6.223**	5.102**	4.448**
Sharpe Ratio	3.362	3.143	3.042	-1.708
SR test Z				-1.633*
Sample (N)	363	363	363	363
R-squared	0.312	0.310	0.324	0.036
Adj R-squared	0.305	0.302	0.316	0.025
F	17.42***	17.90***	17.32***	2.59**
Mean GSV Company Name	-0.737	-0.049	0.788	.

Table 8B: Single sort GSV company portfolio for CAPM & four-factor model (Deciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for GSV company name portfolios constructed deciles. The deciles, GSV1 (Low) up to GSV10 (High), are equally divided based on their mean standardized value of GSV company name (Mean GSV CN). Moreover, the High minus Low (HMLGSV) reflects the zero-investment strategy portfolio, which takes a long (short) position in the highest (lowest) ranked firms in terms of their respective standardized value of GSV. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. Sharpe ratio is presented per individual portfolio, including Memmel's (2003) Z statistic to test the statistical difference for the HMLGSV portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

GSV Company Name Portfolio Alpha (No. of quantiles = 10) (CAPM)											
	GSV1	GSV2	GSV3	GSV4	GSV5	GSV6	GSV7	GSV8	GSV9	GSV10	HMLGSV
Alpha	0.002***	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.548***	0.533***	0.531***	0.523***	0.547***	0.513***	0.545***	0.526***	0.549***	0.548***	0.000
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.02)
GRS	7.210***	6.777***	6.022**	6.481**	4.477**	5.191**	5.610	5.105**	4.632**	5.127**	2.089
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.290	0.298	0.298	0.289	0.307	0.271	0.307	0.296	0.306	0.312	0.000
Adj R^2	0.288	0.296	0.296	0.287	0.305	0.268	0.305	0.294	0.304	0.310	-0.003
F	57.73***	62.98***	62.68***	61.01***	61.00***	56.99***	65.91***	57.33***	63.85***	61.62***	0.00
GSV Company Name Portfolio Alpha (No. of quantiles = 10) (4-factor model)											
	GSV1	GSV2	GSV3	GSV4	GSV5	GSV6	GSV7	GSV8	GSV9	GSV10	HMLGSV
Alpha	0.002***	0.002***	0.002**	0.002***	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.554***	0.542***	0.541***	0.534***	0.562***	0.523***	0.560***	0.545***	0.568***	0.565***	0.011
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.02)
SMB	0.238*	0.210	0.239*	0.270**	0.300**	0.285**	0.264**	0.230*	0.215	0.283**	0.045
	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.05)
HML	0.047	0.045	0.049	0.084	0.101	0.094	0.067	0.068	0.076	0.042	-0.003
	(0.12)	(0.11)	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.05)
MOM	-0.021	0.002	-0.001	0.011	0.024	-0.003	0.025	0.066	0.076	0.029	0.050
	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.03)
GRS	7.886***	7.183***	6.497**	7.090***	4.984**	5.909**	5.954**	5.047**	4.511**	5.353**	2.750*
SR	3.403	3.337	3.211	3.284	2.930	3.046	3.143	3.045	2.961	3.058	-1.456
SR test Z											-1.685**
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.299	0.305	0.307	0.300	0.321	0.284	0.317	0.306	0.315	0.324	0.016
Adj R^2	0.291	0.297	0.299	0.292	0.313	0.276	0.310	0.298	0.307	0.316	0.005
F	16.03***	17.04***	17.38***	17.33***	18.52***	16.82***	18.40***	16.01***	18.06***	16.97***	1.14
Mean GSV CN	-1.119	-0.708	-0.504	-0.325	-0.146	0.041	0.241	0.468	0.753	1.306	.

Table 9A: Single sort GSV composite portfolio for CAPM & four-factor model (Terciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for the overall investor attention (Mean GSV Composite) portfolios constructed terciles. The terciles, GSV1 (Low), GSV2 (Medium), and GSV3 (High), are equally divided based on the mean standardized value of GSV (GSV Composite). Moreover, the High minus Low (HMLGSV) reflects the zero-investment strategy portfolio, which takes a long (short) position in the high (low) ranked firms in terms of their respective standardized value of GSV. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. Sharpe ratio is presented per individual portfolio, including Memmel's (2003) Z statistic to test the statistical difference for the HMLGSV portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

GSV Composite Portfolio Alpha (No. of quantiles = 3) (CAPM)				
	GSV1	GSV2	GSV3	HMLGSV
Alpha	0.002**	0.002**	0.002**	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.529***	0.529***	0.546***	0.018
	(0.07)	(0.07)	(0.07)	(0.01)
GRS	5.409**	5.625**	6.377**	0.331
Sample (N)	363	363	363	363
R-squared	0.297	0.302	0.314	0.008
Adj R-squared	0.295	0.300	0.312	0.005
F	61.68***	61.37***	62.04***	1.94

GSV Composite Portfolio Alpha (No. of quantiles = 3) (4-factor model)				
	GSV1	GSV2	GSV3	HMLGSV
Alpha	0.002**	0.002**	0.002**	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.537***	0.543***	0.565***	0.028**
	(0.07)	(0.07)	(0.07)	(0.01)
SMB	0.229*	0.252*	0.281**	0.052*
	(0.13)	(0.13)	(0.13)	(0.03)
HML	0.052	0.089	0.071	0.021
	(0.12)	(0.11)	(0.12)	(0.03)
MOM	-0.007	0.030	0.047	0.055***
	(0.08)	(0.07)	(0.07)	(0.02)
GRS	5.921**	6.021**	6.592***	0.079
Sharpe Ratio	3.102	3.143	3.277	0.761
SR test Z				0.970
Sample (N)	363	363	363	363
R-squared	0.305	0.313	0.327	0.050
Adj R-squared	0.298	0.305	0.319	0.039
F	17.18***	17.74***	17.59***	4.26***
Mean GSV Composite	-0.592	-0.023	0.616	.

Table 9B: Single sort GSV composite portfolio for CAPM & four-factor model (Deciles)

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the single sorted approach for the overall investor attention (GSV Composite) portfolios constructed deciles. The deciles, GSV1 (Low) up to GSV10 (High), are equally divided based on their mean standardized value of GSV company name (GSV Composite). Moreover, the High minus Low (HMLGSV) reflects the zero-investment strategy portfolio, which takes a long (short) position in the highest (lowest) ranked firms in terms of their respective standardized value of GSV. The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. Sharpe ratio is presented per individual portfolio, including Memmel's (2003) Z statistic to test the statistical difference for the HMLGSV portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

	GSV Composite Portfolio Alpha (No. of quantiles = 10) (CAPM)										
	GSV1	GSV2	GSV3	GSV4	GSV5	GSV6	GSV7	GSV8	GSV9	GSV10	HMLGSV
Alpha	0.002**	0.002**	0.002**	0.002**	0.002***	0.002**	0.002**	0.002**	0.002**	0.002**	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.534***	0.530***	0.525***	0.518***	0.531***	0.535***	0.532***	0.532***	0.541***	0.570***	0.036**
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.02)
GRS	4.384**	5.310**	5.775**	4.414**	7.194***	6.062**	5.029**	6.125**	5.807**	6.139**	0.640
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.290	0.293	0.290	0.288	0.294	0.294	0.305	0.291	0.303	0.322	0.011
Adj R^2	0.288	0.291	0.288	0.286	0.292	0.293	0.304	0.289	0.301	0.320	0.009
F	60.62***	62.00***	59.97***	57.65***	60.62***	61.71***	61.46***	55.92***	58.74***	69.01***	3.94**
	GSV Composite Portfolio Alpha (No. of quantiles = 10) (4-factor model)										
	GSV1	GSV2	GSV3	GSV4	GSV5	GSV6	GSV7	GSV8	GSV9	GSV10	HMLGSV
Alpha	0.002**	0.002**	0.002**	0.002**	0.002***	0.002**	0.002**	0.002**	0.002**	0.002**	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.540***	0.541***	0.529***	0.531***	0.543***	0.551***	0.548***	0.548***	0.561***	0.590***	0.050***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.02)
SMB	0.242*	0.224	0.208	0.227*	0.251*	0.285**	0.261**	0.280**	0.307**	0.255*	0.014
	(0.14)	(0.14)	(0.13)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.14)	(0.05)
HML	0.042	0.032	0.070	0.087	0.113	0.101	0.059	0.088	0.053	0.063	0.022
	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.04)
MOM	-0.028	0.005	-0.016	0.031	0.031	0.039	0.030	0.035	0.043	0.063	0.092***
	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.03)
GRS	4.978**	5.605**	6.436***	4.704**	7.737***	6.479***	5.285**	6.510***	6.009**	6.120**	0.195
SR	2.901	3.082	3.164	2.906	3.402	3.216	3.036	3.225	3.176	3.239	1.025
SR test Z											1.204
N	363	363	363	363	363	363	363	363	363	363	363
R^2	0.299	0.300	0.297	0.296	0.305	0.307	0.316	0.303	0.318	0.333	0.046
Adj R^2	0.291	0.293	0.290	0.289	0.297	0.300	0.309	0.295	0.310	0.325	0.035
F	16.66***	16.96***	17.02***	16.52***	17.83***	18.31***	17.61***	16.06***	16.53***	19.01***	4.49***
Mean GSV Composite	-0.917	-0.570	-0.388	-0.235	-0.093	0.046	0.192	0.360	0.580	1.034	.

Table 11: Double sort ESG-GSV company name portfolio for CAPM & four-factor model

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the double sorted approach for ESG and GSV company name combined portfolios constructed terciles. The terciles for both factors, ESG1 (Low), ESG2 (Medium), and ESG3 (High) as well as GSV1 (Low), GSV2 (Medium), and GSV3 (High) are equally divided based on the mean ESG and standardized value of GSV (Mean GSV CN). The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. The Sharpe ratio is presented per individual portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

ESG-GSV Company Name Portfolio Alpha (No. of quantiles = 3) (CAPM)									
	ESG1-GSV1	ESG1-GSV2	ESG1-GSV3	ESG2-GSV1	ESG2-GSV2	ESG2-GSV3	ESG3-GSV1	ESG3-GSV2	ESG3-GSV3
Alpha	0.002***	0.002***	0.002***	0.002***	0.002**	0.002**	0.001*	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.512***	0.511***	0.532***	0.530***	0.532***	0.538***	0.559***	0.554***	0.549***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
GRS	6.710**	10.185***	10.289***	6.472**	5.039**	7.272***	2.226	3.025*	1.975
N	363	363	363	363	363	363	363	363	363
R^2	0.269	0.263	0.293	0.295	0.298	0.301	0.308	0.307	0.308
Adj R^2	0.267	0.261	0.291	0.293	0.296	0.299	0.306	0.305	0.306
F	51.04***	48.19***	53.36***	63.00***	59.03***	60.15***	67.33***	79.55***	66.52***
ESG-GSV Company Name Portfolio Alpha (No. of quantiles = 3) (4-factor model)									
	ESG1-GSV1	ESG1-GSV2	ESG1-GSV3	ESG2-GSV1	ESG2-GSV2	ESG2-GSV3	ESG3-GSV1	ESG3-GSV2	ESG3-GSV3
Alpha	0.002***	0.002***	0.002***	0.002***	0.002**	0.002**	0.002**	0.001*	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.529***	0.533***	0.560***	0.543***	0.541***	0.560***	0.558***	0.557***	0.555***
	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
SMB	0.322**	0.338**	0.315**	0.237*	0.216*	0.242*	0.165	0.240*	0.207
	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)
HML	0.004	0.082	-0.018	0.067	0.092	0.092	0.078	0.111	0.098
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
MOM	0.004	0.056	0.067	0.028	0.015	0.086	-0.039	-0.024	-0.001
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
GRS	6.842***	10.718***	10.045***	6.997***	5.191**	7.383***	2.815*	3.565*	2.42
SR	3.819	3.695	3.632	3.398	3.138	3.252	2.759	2.400	2.154
N	363	363	363	363	363	363	363	363	363
R^2	0.284	0.280	0.311	0.304	0.306	0.312	0.314	0.318	0.316
Adj R^2	0.276	0.272	0.303	0.296	0.299	0.305	0.307	0.310	0.308
F	14.05***	14.80***	14.70***	18.28***	17.31***	17.27***	18.42***	22.21***	18.57***
Mean ESG	34.98	34.74	35.28	59.26	59.13	59.21	77.91	77.95	78.04
Mean GSV CN	-0.726	-0.057	0.766	-0.717	-0.046	0.776	-0.753	-0.040	0.807

Table 12: Double sort ESG-GSV composite portfolio for CAPM & four-factor model

This table presents the results of the portfolio regressions estimates over the sample period 2013-2019. The asset pricing models, CAPM and the Carhart (1997) four-factor model, are evaluated in the double sorted approach for ESG, and composite GSV combined portfolios constructed terciles. The terciles for both factors, ESG1 (Low), ESG2 (Medium), and ESG3 (High) as well as GSV1 (Low), GSV2 (Medium), and GSV3 (High) are equally divided based on the mean ESG and standardized value of GSV (Mean GSV Composite). The table reveals alpha, the excess returns, per portfolio, and the parameters $R_m - R_f$, SMB, HML, and MOM represent the Fama and French risk factor loadings. Moreover, the GRS statistic tests the efficiency of the asset pricing model per portfolio. The Sharpe ratio is presented per individual portfolio. R-squared measures the proportion of the variance in the dependent explained by the independent variables. The adjusted R-squared is adjusted for the number of predictors in the model. The F-statistic (F) shows the fit of the model by testing equal group means. The 1, 5, and 10% significance levels are indicated by ***, **, *, respectively. Robust standard errors are reported in paratheses.

ESG-GSV Composite Portfolio Alpha (No. of quantiles = 3) (CAPM)									
	ESG1-GSV1	ESG1-GSV2	ESG1-GSV3	ESG2-GSV1	ESG2-GSV2	ESG2-GSV3	ESG3-GSV1	ESG3-GSV2	ESG3-GSV3
Alpha	0.002**	0.002***	0.002***	0.002**	0.002**	0.002***	0.001	0.001*	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.506***	0.511***	0.529***	0.532***	0.524***	0.544***	0.550***	0.555***	0.557***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
GRS	6.710**	10.185***	10.289***	6.472**	5.039**	7.272***	2.226	3.025*	1.975
N	363	363	363	363	363	363	363	363	363
R^2	0.267	0.268	0.282	0.297	0.295	0.304	0.303	0.315	0.310
Adj R^2	0.264	0.266	0.280	0.295	0.293	0.302	0.301	0.313	0.308
F	51.62***	47.28***	51.33***	61.88***	60.06***	60.41***	69.70***	75.14***	68.68***
ESG-GSV Composite Portfolio Alpha (No. of quantiles = 3) (4-factor model)									
	ESG1-GSV1	ESG1-GSV2	ESG1-GSV3	ESG2-GSV1	ESG2-GSV2	ESG2-GSV3	ESG3-GSV1	ESG3-GSV2	ESG3-GSV3
Alpha	0.002**	0.002***	0.002***	0.002***	0.002**	0.002***	0.001	0.001*	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R_m - R_f$	0.523***	0.532***	0.560***	0.539***	0.538***	0.565***	0.550***	0.559***	0.561***
	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
SMB	0.274**	0.340**	0.363***	0.201	0.214	0.275**	0.197	0.206	0.208
	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)
HML	-0.005	0.098	0.001	0.059	0.091	0.111	0.080	0.110	0.096
	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)
MOM	0.016	0.051	0.079	-0.006	0.049	0.078	-0.041	-0.003	-0.013
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
GRS	6.842***	10.718***	10.045***	6.997***	5.191**	7.383***	2.815*	3.565*	2.422
SR	3.312	3.831	3.847	3.286	3.032	3.417	2.403	2.622	2.337
N	363	363	363	363	363	363	363	363	363
R^2	0.278	0.286	0.305	0.303	0.303	0.318	0.311	0.324	0.318
Adj R^2	0.270	0.278	0.297	0.296	0.295	0.310	0.304	0.316	0.310
F	13.90***	14.96***	14.75***	17.62***	17.27***	17.91***	19.45***	21.34***	18.81***
Mean ESG	34.76	34.49	34.98	59.22	59.08	59.19	78.09	77.87	78.03
Mean GSV Composite	-0.594	-0.031	0.608	-0.576	-0.013	0.613	-0.597	-0.028	0.620