DOES POLLUTION MAKE US INVEST MORE SUSTAINABLY?

An investigation of the relationship between New York City's pollution levels and investments in sustainable businesses

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Abstract

The purpose of this study is to investigate how ambient air pollutants in New York City affect investor behaviour, and what the impact on investments in sustainable businesses is. This is done through the construction of four hypotheses utilising ordinary least squares regressions on daily pollution levels, daily stock returns and daily trade activity on S&P 500 companies in the period from January 1st, 2013 through December 31st, 2018. A sensitivity analysis including high versus low ESG portfolios were further constructed to determine potential differences in effects.

Firstly, a connection between air pollutants and the stock market was established through the NYSE Composite Index, discovering a negative correlation on return with effects delayed by two days. Secondly, the relationship was further studied with the inclusion of ESG scores as a sustainability measure for S&P 500 companies. The conclusion was that ESG scores, given the presence of air pollution, is positively correlated with the stock market. This means that an increase in the ESG score would positively affect the expected return. Therefore, contradicting the discussed theory by Merton, arguing that recognition, measured by information, is negatively correlated with a stock's return.

The third part of the analysis studied the different component of the ESG score; environmental, social and governance. This analysis did not prove any significant relationships between these individual scores and stock market returns. Hence, indicating that ESG scores are more used as a comparative measure and not to gain in-depth understanding of a company's ethical profile. The environmental score did however show some significance in high-minus-low ESG portfolios, indicating that this parameter is an intuitive investment choice due to air pollution, compared to social or governance scores.

Lastly, a division into sectors was the foundation for the last part of the analysis. The goal was to determine if some sectors were more heavily invested in during high air pollution. Results proved not to be statistically significant, therefore it is not possible to conclude differences in investments across and within sectors on S&P 500.

This study thereby concludes a negative delayed effect on stock market returns arising from ambient air pollution. Furthermore, a positive relationship between ESG scores and stock market returns, given the presence of ambient air pollution, is established. This indicates that high pollution leads to investment in sustainable companies. When utilising the ESG score as a tool for comparison, this seems to create more value to the investor, relative to the score in itself.

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1 Introduction

Over recent years, sustainable investing has become a buzzword within the world of finance, describing a shift of capital towards companies who seek to address environmental, social and governance issues. What motivates investors to do sustainable investments and how does it differentiate itself from profit-maximizing investing? And is sustainable investment a conscious choice or merely an immediate reaction to the environment surrounding us?

According to a report published by Ernest & Young, sustainable investing is used as a risk mitigator, mainly through reputational and regulatory risk (Tett, 2019). With lower risk comes lower returns as established through classical finance theory. Yet, a study made by Kumar et al. (2016) shows how companies that incorporate environmental, social and governance (ESG) aspects into their long-term corporate strategy, despite lower stock volatility, show higher returns. The worldwide attention surrounding sustainability and sustainable investing will make this discussion even more relevant going forward. It is therefore interesting to study this relationship between sustainability and stock market returns in the financial capital of the world – New York City.

Founded in 1792, New York Stock Exchange has since the end of World War I been the world's largest (Shukla, 2019). Today it continues to play a critical role on the global financial scene, contributing to New York City's prominence. The city is hosting many larger corporate headquarters, making it a busy environment. As in many larger cities, New York City is characterised by a highly dense population and heavy traffic. These characteristics generally contribute to higher levels of pollution, hereby creating general health concerns related to pollution.

Air pollution is one of the greatest killers of the modern age. In 2015 polluted air was responsible for 6.4 million deaths worldwide; 2.8 million from household air pollution and 4.2 million from ambient air pollution (Landrigan, 2017). It is therefore apparent that pollution is a massive concern for human health. However, does this knowledge transfer into investment patterns in sustainable businesses for investors? Is sustainable investment then a conscious choice or merely an environmental reaction?

1.1 Motivation for This Study

The research for this paper is motivated by an interest in exogenous factors impact on behaviour and how these, in extension, affect stock returns regarding sustainable investments. The interesting aspect of this is what motivates the investors' choice – and if it is an immediate reaction to our daily life environment. Do investors invest differently when pollution levels in the air are high and can be felt, smelled, read about or seen? In other words; is ethical investing sometimes an immediate, subconscious or conscious reaction to the world around us?

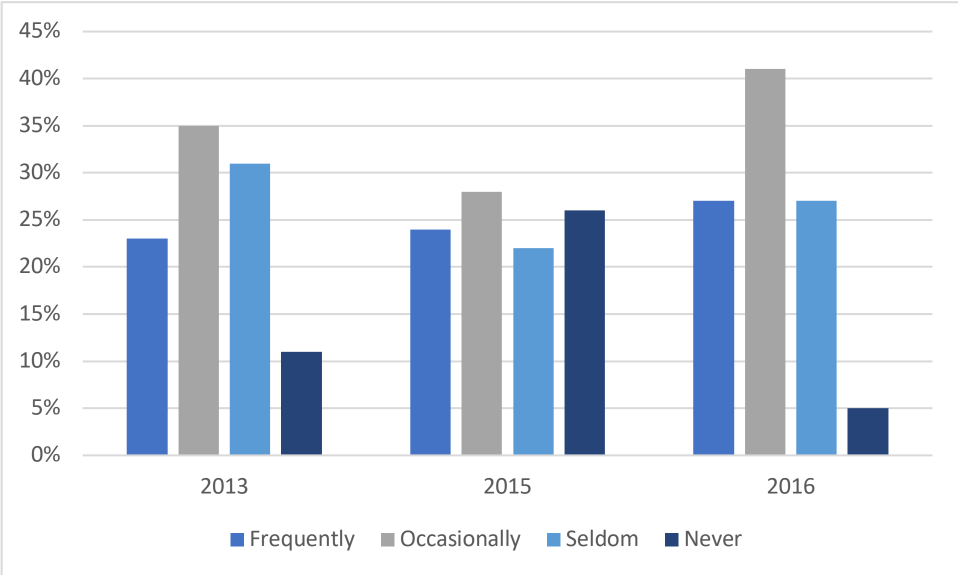
A study conducted in 1988 by Zeidner & Shechter explored peoples' affective reactions to air pollutions. What they discovered was, in case of high levels of perceived pollution, people had an increased willingness to pay in order to reduce the perceived pollution. The main question now is how to identify and communicate pollution as well as the battling hereof. One solution could be a common, widely acknowledged nonfinancial measure – for example the ESG score. A white paper by Donnelley Financial Solutions (2018) describes how there has been an "… *evolution of ESG from niche to mainstream strategy as investors use ESG data as a lens for understanding a company's long-term value and strategy*" (pp. 2).

1.1.1 The Growing Importance of Nonfinancial Data

Classical financial theory explains how individuals are rational and thus only act to maximise their utility. The rational investor weights new and already acquired information, aiming to seek out the most attractive opportunity in the presence of uncertainty (Bayes' rule). Behavioural finance undertakes human financial decision-making differently, stating how individuals are in fact not always rational. Information is evaluated and weighted not as an isolated rational fact, but alongside this persons' views and beliefs. Even though these two financial theories disagree on how individuals make decisions, they both agree on the importance of information. What kind of information does modern-day investors consider when investing?

A report from IBM (2016) explains how financial indicators are no longer sufficient and that cutting-edge organisations are utilising nonfinancial data with great results. Ernest & Young has conducted several surveys among investors, inquiring how frequently a company's nonfinancial performance has influenced their decision-making. Figure 1 depicts how, from 2013 through 2016, there has been a growing trend of investors factoring in nonfinancial data.

Figure 1 - Question Asked: In the past 12 Months, How Frequently has a Company's Nonfinancial Performance Played a Pivotal Role in Your Investment Decision-Making?



Source: Ernest & Young, 2017, pp. 6

This figure shows how 68 percent of the professional investors asked found that a company's nonfinancial performance had, frequently or occasionally, played a role in their decision-making within the last 12 months. Compared to only 52 percent in 2015 and 58 percent in 2013. Thus, it is clear, that nonfinancial data plays a continuously larger role in investment decision-making. This can be attributed to the awareness of other risk factors than the ones apparent in the financial data, but also the continuous increase of capital allocated to younger generations – the millennials.

Above, an increasing significance of nonfinancial data in decision-making has been established, but what could this nonfinancial information be? Many exogenous factors are said to influence the way we invest. Some of these exogenous factors could be related to our surroundings. Examples of nonfinancial data such as this could be weather data such as hours of sunshine, temperature, precipitation and wind speed (IBM, 2016). Ernest & Young describes how a sustainability measure, like the ESG score, has grown in importance due to the linkage between commerce and climate change (Nelson, 2019). This thesis will utilise both weather data and ESG scores as nonfinancial measures, in aiming to explain stock market returns.

1.2 Problem Statement

With foundation in the introduction, explaining why this is both interesting and relevant, an overall problem statement including four underlying hypotheses has been constructed.

How does ambient air pollutants in New York City affect investor behaviour and what is the impact on investments in sustainable businesses?

Here, the first part of the problem statement wishes to establish a connection between behaviour and pollution levels in New York City, and in the presence of a connection, then explore how it affects the market observed through the NYSE Composite Index. The second part of the problem statement examines whether ambient air pollution, either consciously or unconsciously, makes investors invest in more sustainable businesses, proxied by ESG scores from companies on S&P 500.

This type of problem statement is categorized as a problem solving or normative type, as opposed to a descriptive or explanatory type (Rienecker, 2010). Thereby, it is attempted to explain and capture a cause and effect relationship and describing *how* the effect is visible, rather than simply stating a causal relationship.

As mentioned, four hypotheses have been outlined supporting the problem statement by creating concrete guidelines for answering the overall question and divide the thesis into four main sections of analysis.

1. ***Ambient air pollution infers a negative effect on stock market return***
2. ***During periods with high levels of ambient air pollution, stocks with high ESG scores outperform lower scoring stocks***
3. ***The three components of the ESG score (environment, social and governance) weigh differently in importance during decision-making of pollution affected investors***
4. ***Within certain sectors ESG scores weight more heavily on investment decisions relative to other sectors***

The focus of the first hypothesis is to establish a connection between exogenous factors and the market, by building on and examine the relationship between pollution and daily return on NYSE Composite Index. The second, third and fourth hypothesis will all have different portfolio constructions to investigate various aspects of the investment decision. Here, the second hypothesis will examine the relationship between smog levels and sustainable investing proxied by ESG scores with S&P 500 companies. The third and fourth will be based on specific aspects of sustainable investment, measured by the different components of the ESG score and by sector differentiation.

1.3 Structure of Thesis

This thesis consists of two separate parts, a theoretical foundation and an empirical analysis. The theoretical part will act as a foundation and set the analytical framework, whereas the analytical part will explore data and derive empirical results. Initially, section 1 introduced the subject of the thesis, the problem statement and sub research questions, which this thesis aims to answer. Section 1 have additionally explained why this subject is relevant to examine and the motivation behind the thesis. Section 2 consists of a literature review outlining the existing literature within the correlation between ambient air pollution and stock market returns as well as the connection between ESG scores and stock market returns. The last section of the theoretical part, Section 3, is a theoretical walk-through, where classical economic theory and concepts of information among others will be elaborated.

The empirical analysis part of the thesis initiates with section 4, presenting the methodologies implemented into the analysis. Section 5 describes the data acquired and utilised in the analysis. Section 6 conducts the empirical analysis itself, re-presenting the econometric models, the results as well as sub-conclusions derived here from. Section 7 conducts a discussion of the results discovered as well as some potential concerns regarding these. Section 8 will answer the outlined problem statement along the research questions and hereby provide the overall conclusion of the thesis. Lastly, section 9 will suggest topics for further research.

2 Nonfinancial Data and Stock Return

> *"Air pollution is contamination of the indoor or outdoor environment by any chemical, physical or biological agent that modifies the natural characteristics of the atmosphere. … Pollutants of major public health concern include particulate matter, carbon monoxide, ozone, nitrogen dioxide and sulphur dioxide."* (WHO, 2017)

As described by the World Health Organisation (WHO) and discussed by many scientists, air pollution is a threat to human health. Our general wellbeing contributes to setting the scene for the day ahead, dealing with friends, family and co-workers. Imagine being an investor, trading stocks for a living. How will health, partly determined by air pollution, affect the returns of our stock exchanges and daily stock market returns? The sections below will explore this through a correlation between air pollution and health, health and decision-making, and ultimately decision-making and stock market returns. Additionally, a connection between ESG scores and stock market returns will be made, investigating how sustainability consciousness influences investment decisions.

2.1 Air Pollution and Health

Over the last decades, health issues, as a consequence of air pollution, has become an increasingly more debated and researched topic, showing how high concentrations of pollutants can cause heart- and lung diseases. Also, mental and psychological effects on human behaviour have been studied extensively. An American study using longitudinal data from 1999-2011 shows a significant relationship between the air pollutant $PM_{2.5}$ and psychological distress. This study measures the psychological distress using the Kessler Distress Scale (K6) and controls for several demographic and health related factors. They find a clear relationship between the $PM_{2.5}$ concentration and how psychological distressed the individual is, thereby underlining the effect $PM_{2.5}$ has on mental health. (Sass et al., 2017)

One of the great issues with ambient air pollution is, that effects have been seen at very low levels of exposure (Brunekreef & Holgate, 2002). The effects typically associated with ambient air pollution are increased levels of annoyance, stress, depression, anxiety and attention deficit. Bullinger (1989) shows in her research how air pollution does not only affect our physical health, but also our mood and mental health. Her findings yielded area-related effects of air pollution on mood and stress levels, which could have an affect up to four days after exposure. A study conducted in Korea, tested the subjective stress levels in daily life when exposed to ambient air pollution (Hwang et al., 2018). They found that high concentrations of air pollution lead to highly perceived stress levels. Furthermore, this connection became especially prominent in individuals, mainly males, aged 30-64 years – people in the labour active age range.

Stress levels can also be signified through annoyance, as people who are stressed often, show signs of high degrees of annoyance. Rotko et al. (2002) investigated the connection between exposure levels of $PM_{2.5}$ and NO_2 with annoyance. Such an investigation was conducted through surveying random participants from six European cities (Athens, Basel, Milan, Oxford, Prague and Helsinki) on their annoyance levels at home, at work and in traffic. The findings yielded a strong correlation between exposure to high concentrations of particulate matter and the subject's perceived annoyance. An additional study showed how 43 percent (14 percent) of 7,867 surveyed adults across 12 European countries reported moderate (high) annoyance levels when exposed to ambient air pollution (Jacquemin et al., 2007). It further stated that an individual's annoyance could be utilised as a useful measure of perceived ambient air pollution.

When looking into depression and anxiety, a study conducted across the US, sampling more than 4,000 people, showed a clear positive association with $PM_{2.5}$. The participants' mental health was evaluated based on validated, standardised questionnaires and socioeconomic factors such as age, physical health and physical activity, were controlled for. Yet, the study concluded that $PM_{2.5}$ was correlated with both depressive and anxiety symptoms. (Pun, Manjourides, & Suh, 2017) Supporting this discovery is a major literature review conducted by Sram et al. (2017). They explored studies showing correlations between air pollution and the effects on both children and adults. Here increased concentrations of $PM_{2.5}$ was shown to affect adults' cognition, memory and increased depressive disorders. In children they found that pollution inferred changes in behaviour, decrease in IQ as well as an increase in the cases of Attention Deficit Hyperactivity Disorder (ADHD). A consequence hereof is working adults suffering from attention problems and reduced IQ.

The above discussed effects and emotions offset by ambient air pollution exposure can be perceived as negative and draining for the average human being. Based on this above reviewed literature it can be concluded that there is a connection between air pollution and health. In the following this thesis will through elaboration of and determination of this connection, discuss how mood affected by health has a direct impact on individuals' decision-making.

2.2 Health and Decision-Making

Each factor of good or bad health can affect the decision-making of a person in various ways. A person's health will also affect the mood of that person which then directly can affect judgment (Wright & Bower, 1992). In situations where uncertainty regarding a future event is present, judgement, potentially affected by health, can be a deciding factor of the outcome. The Wright and Bower (1992) study showed how happy people are more prone to report high probabilities of positive events and low probabilities of negative events, and vice versa for unhappy people. They

also state how in order to make a subjective evaluation and decision regarding an event or problem at hand, retrieval of information stored in the long-term memory is required.
Mood plays a significant role in the retrieval of information, as it has been shown that people in a bad mood will recall, and thus utilise, a significantly larger amount of negative rather than positive material. Such an effect also becomes evident when studying behaviour regarding risk and loss aversion (Nygren et al., 1996). Positive affect people, as defined by Nygren et al (1996), betted less relative to the control group when facing a potential large loss, even if the risk of such was small. Additionally, the positive affect group gambled more than the control group where the potential loss was smaller, despite the fact that a risk of loss was large.

Health and mood will directly have an influence on the severity with which feelings are perceived as well as what feelings become prominent. Slovic and Peters (2006) find and describe how feelings act as motivators for actions; actions that induce similar feelings, meaning bad feelings provoke actions that produce more negative feelings and vice versa for good feelings. Supporting such a finding is an empirical report exploring induced mood and curiosity. The key finding was that depressed subjects reported less curiosity, a reduced value of information and lack of desire for additional information (Rodrigue, Olson & Markley, 1987). Despite the lack of desire for additional information and the lower value of information, Gardner & Hill (1990) found that people in a bad mood utilise information more in decision-making. This study conducted investigated the impact of mood on necessities, sensory thoughts and informational thoughts. They found that people in a bad mood were more need oriented, meaning the decision-making process was related to needs lower in Maslow's hierarchy, whereas people in a good mood weighted the higher steps higher. Additionally, decision-making in negative people was less affected by sensory thoughts and more by information relative to positive people. Sensory thoughts being thoughts associated with experiences – emotional memories. They thus concluded that negative people are more prone to value necessities and base their decision on information, whereas positive people are more experimental in terms of decisions.
This lack of willingness to venture regarding decision-making, can directly be translated into risk aversion – the lack of willingness to take risks. Thus, a persons' state of health and mood can be directly linked to their risk aversion. For a person, like and investor, who gains and thrives through risk and rewards, a bad mood or negative feelings, for example arisen from bad health, will increase risk aversion as mentioned. It has been shown how a health shock, indicated by certain loss of grip-

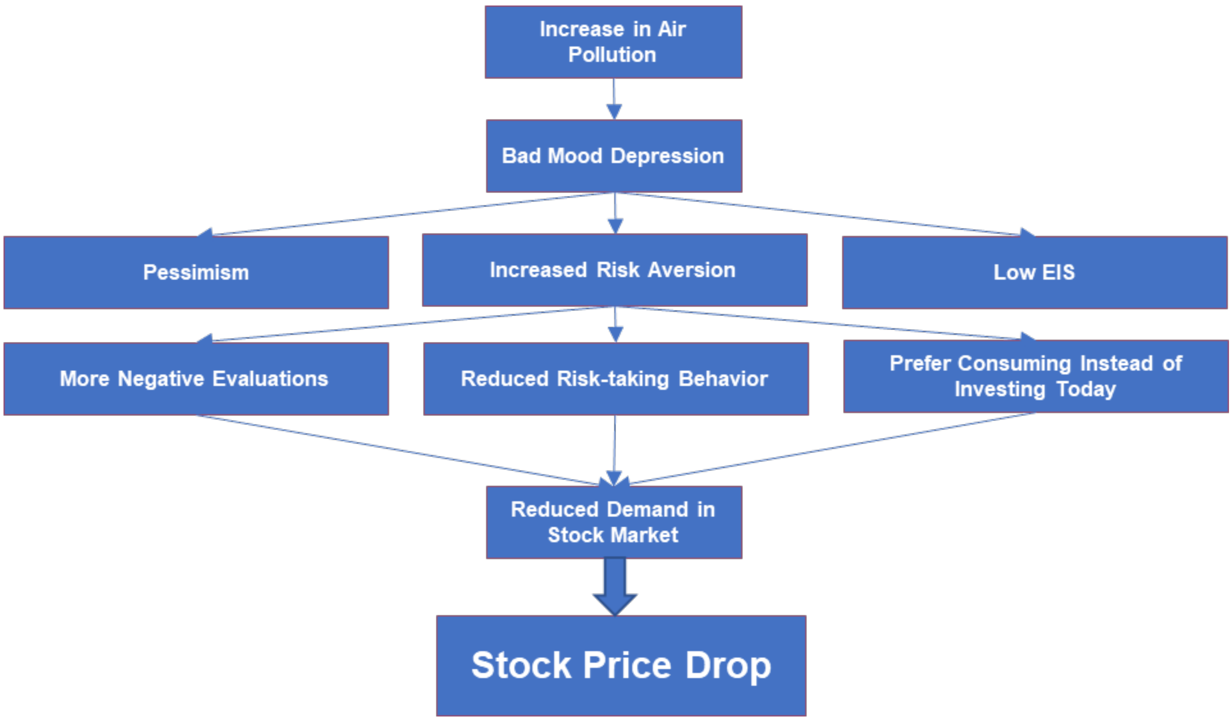
strength, increases individual risk aversion (Decker & Schmitz, 2016). This finding is also, by the authors, proved to possibly last up to four years.

With an offset in the literature discussed, it becomes evident how mood has various effects on individuals' decision-making process. Mood influences the perception of probabilities, the valuation of information as well as the origin and utilisation of it. Furthermore, mood influences the willingness to experiment (i.e. take risks). After having established a linkage between the health and mood of a person and their decision-making, the following section will aim to take this investigation further and show how stock returns are affected.

2.3 Decision-making and Stock Market Returns

A final connection to be established is the one between decision-making and stock market returns. As established in the section above, mood, as a consequence of health, directly affects risk aversion as well as loss aversion which are known to be related to financial decision-making. In the research by Li & Peng (2016), they have established three ways in which air pollution affects mood, which then affects decision-making and ultimately stock market returns (Figure 2).

Figure 2 - Three Channels of the Influence on Stock Prices of Air-Pollution-Induced Bad Mood



Source: Li & Peng, 2016, pp. 3445

The authors, Li & Peng (2016), initiate the model by establishing a connection between the increase in air pollution and bad mood/depression. This project has described the same connection in the two previous sections. Bad mood is seen affecting stock market returns through three avenues; pessimism, increased risk aversion and low elasticity of intertemporal substitution (EIS). Looking at pessimism, when a person is in a bad mood or pessimistic, this person tends to locate new and recall existing negative information rather than positive, as supported by Wright and Bower (1992). Negative information will thus lead to more negative stock valuations as the investor will focus on what drags down the price of the stocks, rather than what might increase it. Investors aim to make a profit from, for example, a low valued stock, which then later will increase in price. When a stock gets valued at a low price and then due to negative impact of information will decrease further in price, ultimately there will be a reduced demand for such a stock. These two effects will ultimately lead to a decline in stock prices.

Gardner & Hill (1990) found that people in a bad mood were less inclined to experiment (i.e. take risks), meaning having a higher aversion towards risk. When increasing a person's risk aversion, a decrease in the willingness to take on risky investments manifest. The lack of willingness to take on risk can lead to a decreased demand on the stock market and ultimately also lead to stock price drop. Lastly, a decreased investor elasticity of intertemporal substitution means that investors are less willing to substitute today's consumption for tomorrow's, ultimately reducing overall investment. The same way lower stock valuations and increased risk aversion lead to a decrease in demand, so does decreased EIS. When the investment activity is reduced, so is the demand, and consequently the stock price.

Supporting the findings of Li & Peng (2016), regarding financial decision-making, is a study conducted by Wong & Carducci (1991) looking into the connection between sensation seeking and financial risk taking in everyday money matters. Firstly, sensation seeking is defined as "*a trait defined by the seeking of varied, novel, complex, and intense sensations and experiences, and the willingness to take physical, social, legal, and financial risks for the sake of such experience*" (Zuckerman, 1994, pp. 27). They found that high sensation seekers displayed higher degrees of risk taking in financial matters. This study was conducted among private people, where a study investigating sensation seeking in hedge funds also found that high sensation seekers took greater investment risk. Yet, the stocks invested in where described as “lottery-like stocks” which meant that those investors did not deliver higher returns, resulting in lower Sharpe ratios. (Brown et al., 2018)

With a foundation in the three paths presented; pessimism, increased risk aversion and low EIS, Li & Peng (2016) found out how bad mood affected the decision-making process, decreasing stock market demand and ultimately resulting in a stock price drop. Wong & Carducci (1991) found that sensation seekers did take higher risks on the stock market, and thus did not take the path of increased risk aversion, but nevertheless also had lower returns.
Hence, this thesis has confirmed how ambient air pollution affects the health and mood of individuals, which then again has an impact on the way decisions are made and finally stock market returns.

2.4 ESG Scores and Stock Market Returns

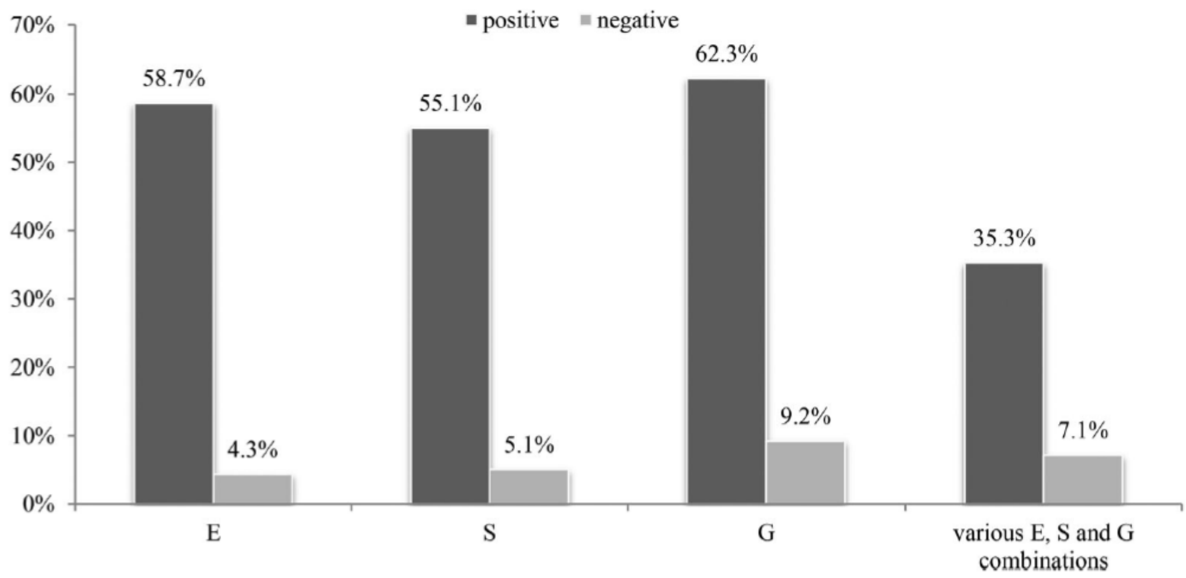
The relationship between sustainability scores and stock market returns has been widely studied, with varying conclusions. This section of the literature review aims to clarify some of these outcomes.

Friede et al. (2015) reviews the results of 2,000 research papers. Their aim is to study the relationship between the company’s ESG score and their corporate financial performance (CFP). The main finding shows that 90 percent of the studies proved a nonnegative correlation between ESG score and CFP measured through a vote count. When studying the 25 meta-analyses included in the sample, the nonnegative correlation decreased to 74.9 percent. Furthermore, they investigate the individual parameters of the ESG score (Figure 3). In doing so, they find the highest positive correlation between the governance parameter and CFP with 62.3 percent of all cases being positive. Yet, if the number of negative studies found is subtracted from the number of positive ones, the environmental score has the highest positive correlation with 54.4 percent positive studies.

An Australian study by Limkriangkrai et al. (2017) studies the effects of the three parameters on both stock return and corporate financing decisions, such as market leverage, dividend yield, book leverage and cash balances. They used data for approximately 200 companies in the period from 2009 to 2014. For each parameter the score has been divided into a rating from one to five based on their performance. Hereafter, portfolios consisting of high scoring companies (rating four or five) were created, and the difference in stock return relative to low scoring companies (rating one or two, zero or one for the governance parameter) studied.

Limkriangkrai et al. (2017) conclude that high scoring portfolios within the social and environmental parameters outperform the low scoring portfolios, based on monthly average stock return, with 0.62 percent and 1.32 percent respectively. The governance parameter shows an opposite effect with a 0.87 percent monthly average return. Results are however only statistically significant for the environmental and governance parameters. When including risk-adjusted measures in the hedged portfolios using Fama-French-Carhart Four factor model, results however change. The parameters no longer show any statistically significant difference in either parameter.

Figure 3 - Vote Count of Positive and Negative Relations Between E, S & G Scores and CFP Across a Sample of 334 Studies



Source: Friede et al., 2015, pp. 222

Investor expectations are a neutral or negative relationship, due to portfolio results, that are exposed to a high degree of various systematic and idiosyncratic risk. Despite this bias, the overall conclusion of the paper is that there exists a positive correlation between a company's ESG score and their corporate financial performance.

Using ESG scores from Sustainalytics, a Canadian study by Sodjahin et al. (2018) finds a negative relationship between ESG scores and stock market returns. The sample consists of 266 firms in the period from 2007 to 2012 and the method follow the Fama-French model (1993). Through either upgrade or downgrade in the firm's E, S or G parameter and the overall ESG score, they study the effect on the stock return. This is done for six subperiods. They conclude, that an upgrade of either of the parameters or the overall ESG score, will have a sustained and negative effect on the stock return. Especially when looking at the late subperiods after the upgrade/downgrade of the score, this negative effect can be observed. The effect is seen in the company's alpha and can last one year after the change. The authors thereby conclude a negative and continuous negative effect of ESG upgrades on the financial performance of the company, arguably due to the lower risk of those companies. They thereby confirm that nonfinancial information plays a pivotal role for investors in their investment decision. (Sodjahin et al., 2018)

A different effect was found by Halbritter & Dorfleitner (2015) who found the effect to be dependent on the rating provider, sample companies and the studied time period. They studied American companies in the period from 2002 to 2011 and included several ESG data providers KLD, ASSET4 and Bloomberg. Their study did not find any significant differences between low and high ESG scoring companies or when examining the different parameters of the score. For KLD data no results proved statistically significant. For Bloomberg data only portfolios consisting of a high social score gained abnormal yearly returns which are statically significant. Furthermore, the high-minus-low portfolios on governance showed negative alphas. From the three data providers, the effect, although not significant, varied greatly in both direction and magnitude.

When using a cross-sectional regression, both ASSET4 and Bloomberg data showed a positive correlation between ESG data and stock market returns. Again, KLD data did not provide any statistically significant results. The authors did however argue, that investors are in fact able to exploit this effect. A division into different sectors did not provide any significant conclusions either.

The study thereby questions the correlation between ESG scores and stock market returns, suggesting a heavy dependability on both data provider and chosen time period.

3 Theoretical Perspective

"The scientific spirit is of more value than its products, and irrationally held truths may be more harmful than reasoned errors."

- Thomas Henry Huxley

(McKaughan & VandeWall, 2018, pp. 1006)

The traditional finance perspective of efficient markets and the rational and utility-maximizing investor will be discussed in this following section. It will also go through behavioural finance concepts that may refute traditional finance assumptions. Furthermore, a model by Robert C. Merton will be presented and discussed in regard to information and neglected stocks. Lastly, an alternative view of explanatory power of potential findings will be discussed using philosopher and author Nassim Nicholas Taleb's notions of randomness with an extension of a discussion of significance in academical research papers by authors Harvey, Lui & Zhu (2016).

3.1 Classical Theory

According to classical economic theory, individuals are rational and utility maximizing (Bodie et al., 2009). The following will briefly go through the efficient market hypothesis, simple supply and demand theory and decision-making according to the efficient market hypothesis.

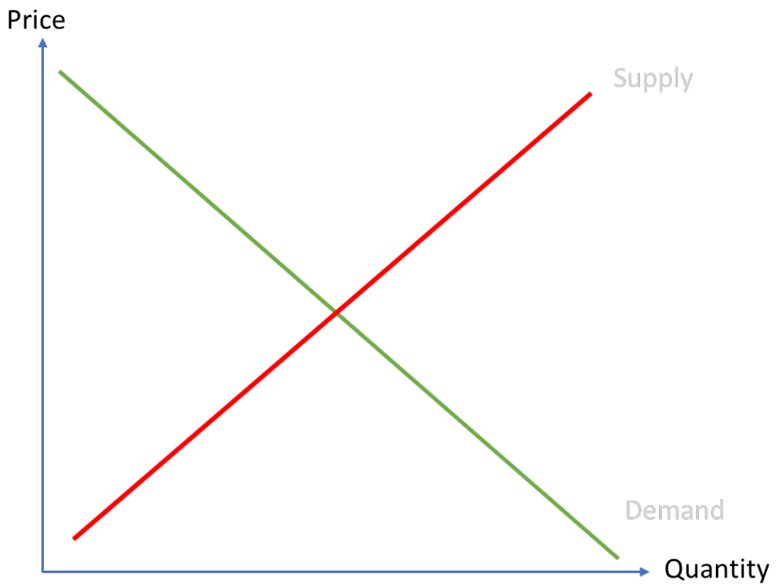
3.1.1 Supply & Demand

It is fundamental to understand the relationship between supply and demand to understand how the market movements affect prices and trade activity. The law of supply and demand is generally used in what is called competitive markets. Competitive markets are marketplaces with a high number of sellers and buyers, such as the stock market. The demand curve shows the relationship between the quantity desired in the market at different prices of the good. Similarly, the supply curve shows the relationship between quantities offered given different price levels. Both supply and demand are determined by a number of factors including the price of goods, buyer taste, prices of other goods, information and more (Perloff, 2012). In this paper, the price of goods and information will be of significant importance.

The law of supply and demand are also applicable to the stock market, where stock prices are determined by availability and request. Thereby prices of the stocks change with the demand, trade activity, and the return for a given stock in such a way that an increased trade activity can lead to a lower return. For this reason, both daily returns and trade activity are included in the econometric models of Hypothesis II, III and IV.

A visualisation of the described relationship between the supply and demand functions can be seen in the figure below (Figure 4).

Figure 4 - Supply and Demand Curve



Source: Own draft

3.1.2 Decision-Making

Within traditional finance, rationality has two meanings; first, individuals adjust their beliefs in accordance with Bayes' rule; secondly, individuals try to maximize utility. Bayes' rule states how individuals update their beliefs with new information in accordance to the formula depicted below:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

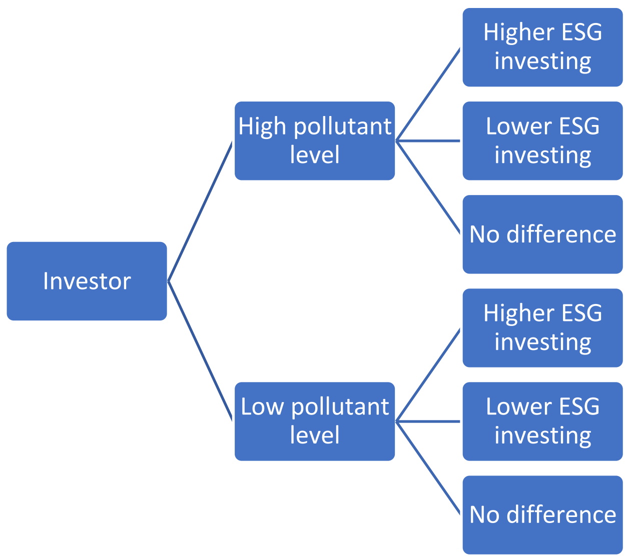
The above formula above shows how new information, B, is processed, given already attained information, A. $P(B|A)$ describes the reversed probability or likelihood of this, meaning the probability of original information, A, being conditional of new information, B. P(A) is simply the probability that the original hypothesis holds and P(B) is the probability that the new information holds as a hypothesis on its own. (CFI, 2019)

To continue, based on their beliefs, individuals make decisions founded on the subjective expected utility, which describes how attractive a decision is to an individual in the presence of uncertainty (Savage, 1954). Building upon previous work by Finetti (1937, as cited in Savage, 1954) and von

Neumann & Morgenstern (1944, as cited in Savage 1954) among others, Savage (1954) developed the concept of subjective utility. Savage (1954) argues that one choice not necessarily leads to one specific outcome and that outcomes depend on the state of the world. There are multiple possible states of the world, where only one of them is true and, this is unknown. Events or consequences of actions depend on which of the states the subset belongs to and responds in accordance to. Furthermore, Savage (1954) presents a preference structure, which represents how an individual evaluates the likelihood of these outcomes. This preference structure is based on the subjective probabilities the individual evaluates for the occurrence of different scenarios.

The foundation of decision-making therefore, according to literature, can be reduced to processing of new as well as already attained information. In relation to this paper, each company's degree of sustainability, proxied by the ESG score, can be seen as the already attained information. Given this information, how does the decision-making change when new information regarding air pollutants is received and how long does it take to be observed in the financial markets given a correlation?
Thereby the study conducted within this paper can be seen as a two-step process as illustrated below (Figure 5):

Figure 5 - Decision Tree Based on Either High or Low Influence of Air Pollutants



Source: Own draft

As seen above, the study of ESG investing, conditional of the pollutant level, is conducted and may lead to one of six different outcomes. Three of these arising from a high level of pollutants on that particular day and three from low levels of pollution. The expectation, as earlier described, is to see a higher ESG investing on high pollution days compared to low pollution days. This decision tree is further developed with Hypothesis III, investigating E, S and G respectively, and further, in Hypothesis IV looking at the different sectors of the S&P 500.

3.1.3 Efficient Market Hypothesis

The previous theorems described rationality from an individual perspective. Hypotheses focusing on the market perspective is, to a certain extent, founded on similar assumptions regarding human behaviour.

According to the efficient market hypothesis (EMH), all available information is already incorporated in the market, which means that assets' fundamental value equals their observed market prices (Bodie et al., 2009). It can be described by a random walk, because today's news is already incorporated in today's prices, they tell no story of what the price will be tomorrow. Tomorrows prices will reflect tomorrow's news and can to the investor appear rather random. (Malkiel, 2003)

The efficient market hypothesis states that:

1. Investors are rational and hence value securities rationally
2. To the extent that some investors are not rational, their trades are random and therefore cancel each other out without affecting prices
3. To the extent that investors are irrational in similar ways, they are met in the market by rational arbitragers who eliminate their influence on prices

Hereby, the EMH claims that investors are not necessarily rational, but that either the market or other investors will adjust for any anomalies that could cause an inefficiency in the market. Mispricing of assets can therefore not persist over longer periods of time (Bodie et al., 2009). Many proclaimers of the EMH would thus argue that investors are not able to beat the market in the long term, and that this in fact is a sign of the hypothesis being true.

The efficient market hypothesis is made up of three degrees of efficiency; weak, semi-strong and strong efficiency. The weak form is defined by stock prices reflecting the historic prices and thereby yesterday's stock price is the best guess of today's stock price. Semi-strong efficiency is characterized by prices in the market reflecting all public available information. Thus, it is not possible to obtain excess returns in the market unless the investor gains insider information. If both public and private information are incorporated into the prices, it is called strong efficiency. Hereby, the investor cannot obtain a competitive advantage in this environment since all information already is incorporated in the prices. (Bodie et al., 2009)

In this paper the efficient market hypothesis will be applied to the significance of ESG scores as information. It will be explored whether ESG scores indeed serve as information, but also if the different pollution levels serve as information and how and when it is observable in the stock market.

3.2 Anomalies

Behavioural finance is, in comparison to traditional finance, a relatively new field. It has nevertheless established itself with much evidence of its existence through several studies proving that humans in fact are not always rational (Richard Thaler, Daniel Kahneman and Matthew Rabin). Its roots can be found in psychology, which studies human decision-making, judgement and wellbeing; concepts all relatively unexplored in the field of traditional finance (Dellavigna, 2009).

Insurance and lotteries could be examples of irrationality existing in not only financial markets but in broad society. If individuals were fully rational, insurance of small objects such as glasses or electronics would not exist. Economic theory would argue that insurance of such small objects is insignificant when valuing your life's total financial value and it would give you an unreasonable elevated risk aversion. When insuring such items, it would seem that individuals take their current situations more into consideration than their total life's worth. This particular topic is called mental accounting and Richard Thaler (1999) describes this as follows:

"The set of cognitive operations used by individuals and households to organize, evaluate and keep track of financial activities." (Thaler, 1999, pp. 1)

The above description does not necessarily imply irrationality. It does however imply that a set of cognitive operations determines how we organize our financial decisions.

Another industry which shows signs of irrationality is the gaming industry, with a particular focus on lotteries. By default, participating in lotteries is irrational. They have, on average, a negative expected return and thus a rational individual would never play. Yet, the gaming industry does in fact exist, and some might say flourish, meaning something irrational must drive humans to participate in such games. Gambling professor Robert Williams argues, that humans in general have difficulties with small probabilities. A probability of 1 to 50 million or 1 to 5 million are vastly different probabilities but might be closely related to individuals buying the lottery tickets (Lebowitz, 2016).

3.2.1 Risk Aversion and Conservatism Bias

In this paper, two behavioural concepts will be used; conservatism bias and risk aversion. The first concept concerns itself with how individuals update information, which is a general theme throughout this thesis. The second concept of risk aversion is included because Li & Peng (2016) established a direct relationship between air pollution and risk aversion in the market.

A conservatism bias describes the situation when an individual cling to past knowledge instead of acknowledging newer evidence and taking this into account in their decision-making. In other words, an individual failed to update his/her knowledge and thus make decisions based on outdated information. This causes the investor to underreact to market news. (Pompian, 2015)

Studies show that when investors do update their information, they react slowly to market news, which can then be exploited by other investors. For example, conservatism biased investors have a tendency to sell losing stock too slowly, because their previous decisions on buying the stock still lingers in their mind. On the other hand, easily processed information may cause an overreaction in the investor. Easily processed information could for example be actual examples or scenarios playing out. (Pompian, 2015)

The conservatism bias defies Bayes' rule on how individuals update their beliefs, as it may seem that it is not done as effectively, or efficient as traditional finance claims it will.

Risk aversion is a well-established concept within behavioural finance. It is built on the fact that some individuals dislike risk so much that they would decline games even with small or insignificant probabilities of losing. Thereby, there is a disproportional utility of winning and losing the same amount of money, meaning individuals have a decreasing marginal utility. (Kaas et al., 2001)

3.3 Information

"Although I must confess to a traditional view on the central role of rational behaviour in finance, I also believe that financial models based on frictionless markets and complete information are often inadequate to capture the complexity of rationality in action." (Merton, 1987, pp. 484)

This section will primarily focus on the paper "*A Simple Model of Capital Market Equilibrium with Incomplete Information"* (1987) by Robert C. Merton.

Robert C. Merton (1944 -) is a distinguished American professor, economist and Nobel Prize Winner, and PhD from Massachusetts Institute of Technology (Merton, 2019). Through his career, he has published several prominent research papers, among others the one used for this paper. In his paper, Merton describes the market given incomplete information. He therefore challenges the classical finance theory stating complete and equal amount of information among investors. The focus for this paper will especially be on neglected stocks, meaning stocks that are less known to investors.

"Perhaps the most controversial conclusion of our model is that less well-known stocks of firms with smaller investor bases tend to have relatively larger expected returns than in the comparable complete-information model." (Merton, 1987, pp. 507)

Through his paper Merton proves that investor recognition is positively related to firm value, holding other fundamentals constant. The paper and this thesis are aligned on the premise that there is diverse and incomplete information in the market, where ESG scores represent the transparency of information a firm holds. This means that neglected stocks could be considered low ESG scoring companies in regard to this thesis. However, this thesis will only indirectly study whether these stocks are undervalued by comparing trade activity and daily return of high and low ESG scoring companies. This paper will further extend Merton's perspective by including an external factor which may contribute to the investment decision – air pollution. It could be assumed that high amounts of pollution, and the awareness hereof, may make investors neglect certain highly polluting companies to a higher degree relative to low pollution days. Thus, assuming that neglected stocks are undervalued regardless of pollution level.

"*In summary, financial markets dominated by rational agents may nevertheless produce anomalous behaviour relate to the perfect-market model.*" (Merton, 1987, pp. 508)

In other words, this thesis studies whether investors invest in what can be considered an ethical manner, and if air pollution may affect the way they trade in one direction or another.

3.3.1 The Model of Incomplete Information

The model of the study is presented below and describes a two-period market equilibrium model given incomplete information (Merton, 1987). Only the most essential formulas and definitions relevant for this thesis and the understanding of the model are included in this chapter. Proofs et cetera will therefore not be examined here.

The model assumes active investors that invest based on a mean-variance efficiency. Each investor only has information on a subset of stocks. Equilibrium is studied based on the incomplete information in the subsets of securities. End-of-month cash flow for *n* firms is given by:

$$\tilde{C}_k = I_k[\mu_k + a_k\tilde{Y} + s_k\tilde{\varepsilon}_k]$$

I_k describes the amount of physical investment in firm k. Furthermore, the firm's production technology is included in the model and is given by the parameters μ_k, α_k and s_k. $\tilde{Y}$ is a random variable.

The equilibrium returns per dollar invested in a firm *k* over a period is given by:

$$\tilde{R}_k = \bar{R}_k + b_k\tilde{Y} + \sigma_k\tilde{\epsilon}_k$$

In which:

$\bar{R}_k = E(\tilde{R}_k) = I_k\mu_k/V_k$, *$V_k$ describes the equilibrium value of firm k at the beginning of the period.*

$b_k = a_k I_k/V_k$

$\sigma_k = s_k I_k/V_k$

$k = 1, \ldots, n$

Investors in this economy choose their optimal portfolio based on Markowitz-Tobin's mean-variance and looks like:

$$U_j = E\left(\tilde{R}^j W^j\right) - \frac{\delta_j}{2W^j} Var(\tilde{R}^j W^j)$$

In which:

W^j *is the investors' original amount of shares' value in equilibrium prices*

$\tilde{R}^j$ *is the investors portfolio expected return per dollar*

$\delta_j > 0$

$j = 1, \ldots, N$

Each investor holds the following information about firm *k*:

1. Return on the riskless security
2. Expected return and variance of a forward contract security
3. Basic structure of securities return

Informed investors know about the parameters $\bar{R}_k, b_k$ *and* σ_k^2 in the given security (*k*). As an assumption for the model, every informed investor has an equal amount of information about the stock. Merton (1987) points out asymmetric information could, in reality, infer that both individual and institutional investors not investing in smaller companies with a smaller shareholder base.

Following the assumptions, the predictions looks the following:

$$\frac{\partial a_k}{\partial \sigma_k^2} = \delta(1 - q_k)x_k / q_k$$

$$\frac{\partial a_k}{\partial x_k} = \delta(1 - q_k)\sigma_k^2 / q_k$$

$$\frac{\partial a_k}{\partial q_k} = -\delta x_k \sigma_k^2 / q_k^2$$

In which:

a_k: represent a parameter of the firm's production technology.

σ_k*: described above. Is the product of investment in firm K (I_k) and a parameter of the production technology in firm K (s_k) divided by the value of the firm (V_k)*

q_k*: represent the investor recognition through the equation* N_k/N*. Thereby describing the fraction that knows about firm k, because N_K is the amount of investor that knows about firm k, and N is all investors.*

x_k*: is given by* $x_k = q_k \Delta_k / \delta \sigma_k^2$ *and is an exposure level to common factors. The common factor is a part of a stock's return, that influence a wide range of stocks, such as firm-specific return variance and relative size of firm.*

The first part explains that given the same market risk, companies with larger firm-specific variance will also have a larger company alpha. The second part explains that given companies have the same volatility and investor recognition, the company that is relatively larger, will have a larger alpha. The last part equation states that companies will have lower alphas if they are more widely known (higher investor recognition) and has a higher investor base. This means that the value of the security is increasing with investor recognition, but high investor recognition will lead to a lower expected return. Both relationships will increase with the firm specific risk. It is the last prediction that is of special interest for this paper.

Merton (1987) further describes how transmitting information from the company to the investor may be costly and describes transmitting the following way:

"*For Party A to convey useful information to Party B, requires not only that Party A has a transmitter and sends an accurate message, but also that Party B has a receiver. If an investor does not follow a particular firm, then an earnings or other specific announcement about that firm is not likely to cause that investor to take a position in the firm."* (Merton, 1987, pp. 489)

In the above quote, Merton (1987) describes sending information from the company, is not one-sided. It requires that the investor already has some knowledge or is aware of the company's existence in order to track new information. In this thesis, the above potential bias is avoided by studying large American companies, represented by S&P 500. This leads to assume that almost all investors, both institutional and individual, have knowledge about if not all, then a large number of these companies.

Merton (1987) considers a stock neglected if less information is available about that particular stock, which corresponds to a small value of q_k in the model. According to his model, investors all trade in securities they have the most information about, and therefore higher return could be achieved investing in the neglected stock. The most widely known stocks will have a q_k value of close to one.

Merton (1987) concludes that it is not necessary to divert far from classical finance theory in order to include incomplete information. He further concludes that if neglected stocks could easily be identified, "*a professional money manager could improve performance by following a mechanical investment strategy tilted toward these stocks*." (Merton, 1987, pp. 507)

In this thesis, the neglected stocks would be companies with a low ESG score. They have less transparency in their information, and according to Merton therefore trade less, because they are overlooked.

3.3.2 Institutional or Private Investors?

In one study applying Merton's model, by Hong & Kacperczyk, (2009), it is suggested that social norms might play a larger role for institutional investors in the investment of sinful companies. They define neglected stocks as stocks within what could be considered unethical industries, such as tobacco, alcohol, gaming, nuclear energy and weapons. This thesis will view these types of stocks in a different manner, not focusing on sinful industries, but instead on companies with low ESG rating, meaning either low scores within environmental, social or governance aspects of their business. It could also be viewed in relation to sectors, with some sectors being more widely known and invested in relative to other sectors.

Institutional investors might be bound by the overall image of the institution they are representing in their investments. Thereby it might cause reputational damage for the institution if it heavily invests in for example the weapon industry. Private investors, on the other hand, face less scrutiny as they can invest in sinful industries without severe reputational damage by not having their trading information as public information. Merton's (1987) study focuses primarily on private investors.

It should also be noted in the model, that social norms are not only time dependent but also regional dependent. This means that countries may vary in what is considered most and least unethical. This is proven by a study by van Neuen in 2018 and Salaber in 2009.

3.3.3 Investor Recognition

The importance of Merton's paper for this thesis mainly lies with the concept of investor recognition. Only indirectly mentioned in the paper but emphasised is his belief is that an increase in investor base increases the value of the firm. Therefore, a firm, that wishes to increase investment, should focus on increasing the investor base, thereby increasing investor recognition.

3.3.4 Expectations

In many ways Merton's theory is quite the opposite of the premise of this paper. He states that lesser known stocks outperform more well-known stocks. All companies included in this thesis can be argued to be well known stocks as they are all part of the S&P 500 and thus represent some of the biggest companies in the United States. It can however be argued that some companies, even on S&P 500, are more widely known than others and receive more analytical coverage.

It can be argued that the effect of the neglected stocks has disappeared through time because it has been exploited by investors. This was the particular conclusion from Beard & Sias (1997) that found no effect across more than 7,000 companies in the period from 1982 to 1995.

The expectation of this thesis is however, that companies with high ESG scores will outperform those with low ESG scores, and that this effect will be accentuated on days with high pollution levels. Therefore, the expectations are quite the opposite of Merton's model.

3.4 Pure randomness?

Although behavioural finance can explain many anomalies within the market, it cannot explain every event. For example, a financial bubble shows a market mispricing, but it cannot be explained purely rationally or by the help of the behavioural field. It is still fairly difficult detecting or predicting a bubble, before it bursts.

Nassim Nicholas Taleb (1960 -), an American Lebanese author and philosopher, contributes to the existing literature with two significant concepts relevant for this thesis; randomness and asymmetry. Taleb (2007) argues that individuals in general tend to detect patterns when in fact it is just a random roll of dice. He believes that sciences, as well as markets, have an overweight of determinism that makes us unequipped to perceive alternative explanations or outcomes to a given situation. Bear and bull markets are zoology terms to him, and he believes that if all conceived financial markets the way he does, they would not exist.

3.4.1 The Rare Event and a Turkey

Taleb (2007) questions the use of time series within the financial market's analysis. He argues that the past it not always the best predictor for the future, which may be influenced heavily by randomness. He claims that society studies the past so hard that patterns are stumbled upon perhaps out of sheer chance. This way of deriving, potentially non-existent, patterns from historical data, Taleb (2007) calls a hindsight bias.

Furthermore, he states the importance of outliers. According to Taleb (2007), outliers are often overlooked or consciously extracted from observation because they might skew the data. In doing so, little value is placed on the rare event, although it might be an important event in the dataset.

Overall, according to the author, the point is to avoid being a turkey. The author illustrates this problem of depending too much on observations to describe a broader context and ignoring the rare events, with the help of a turkey. He describes how a turkey that is fed every day by humans would have a friendly view on humans and simply expects that they will also feed it tomorrow and the day after. Because of what has already happened, the turkey does not anticipate any changes. But then it becomes Thanksgiving which will turn out to be mortally fateful for the turkey. It did not foresee this event and had no tools to do so. Thereby, it could not blindly trust that that the events of yesterday will extend to tomorrow. The turkey represents the problem Taleb (2007) sees with time series analysis.

The above considerations lead to one of Talebs' (2007) main points; the problem of induction. The problem of induction refers to the problem with generalising based on an analysis conducted on a sample. He thus believes, that academics should be careful using induction in studies, meaning being too quick to use specific studies, or samples, to conclude something about the entire population. In the above example, the turkey is so heavily dependent on the sample of the past, concluding that it will be fed and live happily, that it never predicts the rare event – Thanksgiving.

This thesis will thus be aware of hindsight bias as well as the problem of induction when conducting the analysis. Furthermore, it will be discussed further in connection with the empirical results.

3.4.2 Asymmetric Probabilities and Outcomes

Events and frequencies in which they occur is an essential aspect in probability math, however, often misunderstood or overlooked. Asked whether he believes the market will go up or down, Taleb (2007) answers that he hopes it will go up but think it will go down. A curious listener thereafter asked if he does not in fact have a heavy short position in the market.

The aspects the crowd were not able to conceptualize at first was that of asymmetric probabilities. This concept describes a setting, where the probability of two or more outcomes are not equal. When asked, Taleb (2007) believed that that the market might go up and feared it might go down in spite of his short position. He believed in fact, that if the market went up, it would not be to the same extent as it might be if it went down. Thus, the asymmetric probability lies within the fact that the probability of the market going up is not equal to the probability of the market going down.

The asymmetric probabilities do not in themselves determine the expectations for the market. By multiplying the probabilities with the outcomes, one gets the expectations. Taleb (2007) also discusses asymmetric outcomes, which is a setting where the outcome of two or more probabilities are not equal. In the above example, the asymmetric outcomes are represented by the extent of which the market goes up or down not being equal.

In this thesis, it is expected that the effects of pollution may not affect investors the same way on high and low pollution days; there might an asymmetric effect. Furthermore, there could also be an asymmetry between the effects seen on low and high ESG scoring companies. Thus, the asymmetric probabilities are the difference in occurrence of high and low pollution days, and the asymmetric outcomes are the differences in impacts on investors and companies. This will be explored further in the analysis and discussion.

3.4.3 Ergodicity

Ergodicity is a statistical term used by Taleb (2007) to state that time will erase what could look like patterns evidently to randomness. "*Remember that no one accepts randomness in his own success, only in his failure.*" (Taleb, 2007, pp. 157). What may seem as trends, or solid time continuing high return, is for Taleb (2007) simply randomness, and will lead to ergodicity, meaning that the high returns will flatten out over time or maybe even becme negative.

Taleb (2007) connects ergodicity to a behavioural concept; survivorship bias. He claims that when studying an investor and his/her profits in the past, it is not relevant to look merely at the investor himself/herself; the population the investor came from must also be studied. This claim makes the population size essential for any characteristics of the individuals in the group. For this thesis, it merely looks at just under 500 companies, which cannot be a representation for the entire population, which can be said to be every listed company in the world.

Taleb (2007) further extends the idea with what he calls data snooping. He argues that data is often fitted to suit the rule and not the other way around, as it should be.

"The more I try, the more likely, by mere luck, to find a rule that worked on past data. A random series will always present some detectable pattern. I am convinced that there exists a tradable security in the Western world that would be 100 % correlated with the changes in temperature in Ulan Bator, Mongolia." (Taleb, 2007, pp. 162)

Hereby, Taleb (2007) describes that if you search long enough you will find correlations between what appears to be completely unrelated variables by randomness. This concept of data snooping will be extended in the following section.

3.5 A Significant Discussion

"*…a t-statistic of 2.0 is no longer appropriate – even for factors that are derived from theory".* (Harvey, Lui & Zhu, 2016, pp. 37)

This part of the section will be founded on the paper by Harvey, Lui and Zhu (2016). The paper questions what can be considered significant in today's academia. The question arises due to large amounts of data mining, that may lead to significance based on randomness. In order to overcome this, the authors suggest that a new cut-off level for the t-statistic. It should be increased from 2.0 to 3.0 when used in the framework for asset pricing. They study 313 research papers regarding cross-sectional patterns of returns, mainly papers introducing, and testing factors related to equity, with a total of 316 different factors. This is done to both re-evaluate those conclusions and to set a new statistical framework going forward.

Harvey, Lui & Zhu (2016) argue that many factors, especially reasonably new ones, could be significant by chance, simply because of data mining and large amounts of already existing factors. According to the paper, the significance level should change over time and therefore they do not suggest a rigid change, but instead a fluid increase correlated with time and number of new factors.

The authors state three reasons for stricter significant criteria today:

1. The possibility of discovering new factors has most likely decreased
2. Limitations to the amount of data available for study in finance
3. Data mining has increased, as cost has gone down

The paper finds that, dependent on cut-off value used, the highest amount that could be falsified was 158 out of 296 factors. Therefore, the paper suggests creating a new significance level of 3.0, which argued might also be too low, but is due to the factors included in the research paper. Based on this discovery and discussion, this thesis will evaluate the significant empirical results from the analysis with this perspective.

3.6 Conclusion

The relevant theories for the topic in question have been presented, which are mainly related to information and methodology. Additionally, it included a discussion of information in the market in relation to Merton's (1987) idea about neglected stocks, efficient market hypothesis and conservatism bias. Introducing assumptions which creates a foundation for traditional finance. However, also touching upon anomalies in the market and how observations cannot always be explained using the traditional finance paradigm, e.g. Taleb (2007).

According to Taleb (2007) irrationality is a result of an excess degree of determinism and not enough weight on randomness. This will further be discussed in later chapters. In extension of Taleb (2007) the section also included a brief discussion of what can be considered significant in a time with excessive data mining.

These different theories are prone to different expectations to what conclusions this thesis might reach. In regard to Merton, it would be expected to find a higher return on what is considered neglected stocks – companies with a low ESG score. From a behavioural standpoint, risk aversion would suggest that investors would focus more on high ESG scoring companies in risk avoidance, thereby excepting a lower return.

Thereby this section can be developed further using empirical data to discuss the relationship between randomness versus causality, the role of information, and awareness versus unawareness.

4 Methodology

This projects' methodical foundation will be outlined in this section, including explanations of the main objective and assumptions of the thesis, empirical framework and research design.

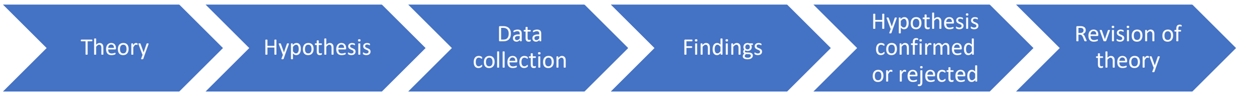
4.1 Main Objective

Examining the connection between ambient air pollution in New York City and investor behaviour, as well as the implications of this behaviour on sustainable businesses is the main objective of this thesis. Sustainable investing, measured by ESG scores, will also be examined in relation to the pollution levels, to determine whether investors trade more sustainably on high pollution days compared to low pollution days. This will subsequently lead to a discussion of results in lieu of the theory discussed, with a special focus on Merton (1987) and Taleb (2007).

Adopting the deductive study method in this thesis, means that the foundation of this study builds upon underlying assumptions and hypotheses attempting tested with empirical data (Bøgh Andersen & Watt Boolsen, 2015). The main research method in the deductive method is falsification or acceptance the hypothesis via observations. Being able to accept or falsify a hypothesis is dependent on whether the main data is quantitative or qualitative and which scientific theoretical foundation the project has (Bøgh Andersen & Watt Boolsen, 2015).

The processes of the deductive research design follow the outlined process below (Figure 6):

Figure 6 - The Deductive Research Design



Source: Bryman, 2012, pp. 10

This thesis is motivated by previous literature in the field, discussed in section 1. This has created foundation of four hypotheses, that through data collection is confirmed or rejected. Thus, leading to a discussion of theory and whether conclusions differ from or correspond to previous research.

4.2 Quantitative Research

There are four main concepts related to the quantitative research design:

- Measurement
- Causality
- Generalization
- Replication

One of the aspects that must be taken into consideration is the question of causality. Is it in fact possible to prove a relationship between pollution and the stock market, or are there any other underlying measures, not included in this model, which could explain the stock market returns? This is an example of an omitted variable bias. An omitted variable bias is when relevant measures are omitted and thus effects are attributed to included variables. Omitted variable bias have to do with the internal validity of the paper, whereas external validity is concerned with if the study can be generalized to a broader context. (Bryman, 2012) An important factor in this thesis, and also related to external validity, is the aspect of generalization. The objective is to conclude something that can be generalized not only for New York City or the United States, but for other cities with high pollution levels as well. Replication is also an important part, since it can provide evidence against research biases if the results can be replicated by other researchers.

Other key concepts in quantitative studies are reliability and validity. Reliability refers to consistency of measures, whereas validity refers to whether the measures chosen in fact measure the concept investigated (Bryman, 2012). That could for example be correlations and other ways the measures may not work together (Bryman, 2012). In this relation the weather data may prove the most significant challenge, as they might not be fitting control variables for the pollution levels.

4.3 Paradigms

Social science has four basic interests:

- Explain/predict
- Understand/explain
- Set free
- Deconstruct

Where the first interest encompass positivism, experimental research etc., the second is phenomenology, hermeneutics and symbolic interactionism. The third builds on critical theory, Marxism and some aspects of feminism. Lastly, is among others postmodernism, poststructuralism and queer theory (Brinkmann, 2015).

This project will be based on two of the four presented interests; explain/predict and understand/explain. It has further been narrowed down to the perspectives of phenomenology, hermeneutics and positivism. Of these, hermeneutics will serve as the foundation of how knowledge is understood in the project.

4.3.1 Hermeneutics

Primary knowledge and information search are based on the hermeneutical paradigm. This implies that the authors, before researching the topic, have a preunderstanding of the topic which becomes apparent through the hypothesis explaining the relationship between pollution and behaviour. A preunderstanding is a necessity for obtaining an understanding of a particular topic. (Bøgh Andersen & Watt Boolsen, 2015)

A key element to hermeneutics is that knowledge is never complete. In other words; an individual will never reach the end of the circle, because they can always reach a higher level of understanding. The hermeneutic perspective's main task is to acknowledge, rather than explain. Since the focus is on acknowledging, and this is an infinite process, a constant and objective truth will never be gained. The truth will keep changing as more knowledge and further understanding is added on. (Berg-Sørensen, 2012) Therefore, the truth this thesis attempts to create will not be stagnate or universal. Throughout the process, this thesis attempts to challenge the preunderstanding and thereby rise a level in the hermeneutical circle to attain a new preunderstanding. Hence, this process will never end, and the end of the spiral shall never be reached but only moved higher up in understanding and learning. This also implicates that the subject will change slightly the more knowledge is gained.

The hypotheses are a way of making existing knowledge on the topic concrete and create the connection between theory and empirical data. This further aids in limiting the topic where necessary (Bøgh Andersen & Watt Boolsen, 2015). The hypotheses thereby represent the authors' preunderstanding of the topic and creates foundation for the way the topic is approached.

Another element of the hermeneutics approach is the relationship between different parts and the whole. Explaining the whole without the parts cannot be attempted, as the parts cannot be explained without an understanding of the whole. It is through this interaction that knowledge is obtained (Berg-Sørensen 2012). This will be done by not only looking at the data as arguments for the obtained results, but also having the macroeconomic perspective on why the data is as it is. Furthermore, an acknowledgement of alternative views on the data process is discussed in the theory section.

4.4 Econometrics

To conduct multiple linear regressions, the statistical program R is used. The R code can be found in the appendix. Linear regressions as a method is used, since the aim is to study the linear relationship between air pollutants, stock market returns and trade activity in relation to sustainability.

4.4.1 Ordinary Least Squares

As the focus of this study is not to investigate the developments over time, but rather prove the existence of a connection between pollution and the stock market, regardless of time, the ordinary least square method (OLS) will be used, instead of a time series. As later described in the data description, independent and dependent variables are all continuous. However, some control variables are dummy variables, meaning they will take a value of either zero or one if the statement of the dummy is false or true respectively.

A simple linear regression has the foundational form as presented below:

$$y_i = \alpha + \beta * x_i + \varepsilon_i$$

The dependent variable, y_i, is given on the left hand-side of the equation. Alpha is a constant variable in the model and beta describes the relationship between the dependent and independent (x_i) variable. The value of beta states the magnitude of the impact the independent variable has on the dependent one, where the sign of beta states the direction of the relationship. Finally, epsilon, ε_i, is the regression's error term which is a residual variable inferring the model not fully representing the true relationship between the independent variables and the dependent variable.

The OLS regression fits the model to data by taking the square of the difference between the observed values and a perfectly linear line, also known as the residuals. Thereby, the model calculates and accommodates for the deviations of the observations to a fitted line. (Stock & Watson, 2015)

4.4.1.1 Assumptions

OLS regression are based on below listed assumptions:

1. Error term has a mean of zero
2. Uncorrelated error term
3. No large outliers
4. Error term is not correlated with the independent variables
5. No heteroscedasticity
6. No perfect linearity between two or more independent variables

(Stock & Watson, 2015)

The first assumption states that the population error term of the regression has to have a mean of zero. This error term represents the dependent variable independently of the independent variable. If the error term of the dependent variable did not have the mean of zero, the model would either overpredict or underpredict the results. The second assumption is also called autocorrelation. This means that if the error term is correlated with itself and that one value can be used to predict the next, something might be missing from the model itself. This could be solved with another independent variable to capture this information. (Stock & Watson, 2015)

In order to achieve the most significant estimates of the OLS regression, there should be no large outliers as it may skew the results. The more outliers are observed, the less linear the model becomes as the linear relationship no longer fits data. The fourth assumptions states that the error term cannot be correlated with the independent variables. If it were so, the error term would no longer be random, as the independent variables could be used to predict the error term. (Stock & Watson, 2015)

Heteroscedasticity refers to the error term not having a constant variance, where homoscedasticity refers to a constant variance. If heteroscedasticity is present it will make the regression estimates less precise. Having two or more independent variables perfectly or almost perfectly correlated with each other is called multicollinearity. A perfect correlation between two variables could suggest that they are explaining the same thing. Having two variables almost perfectly correlated would just like the prior assumption decrease the precision of estimates. (Stock & Watson, 2015)

4.4.2 Lags of Variables

Since the study focuses on changes in behaviour it is necessary to examine the lags of both independent variables and control variables alike. Several exogenous factors may not have an immediate effect on investor behaviour, such as pollution, whose impact might not be apparent until several days later. As the market is only open from Monday through Friday every week, the focus is on the exposure to pollution occurring on weekdays. Lagging weather and pollution data therefore means that Monday data will be lagged to Friday, omitting the weekend.

4.4.3 Omitted Variable Bias

"*If the regressor is correlated with a variable that has been omitted from the analysis and that determines, in part, the dependent variable, then the OLS regressor estimator will have omitted variable bias*." (Stock & Watson, 2015, pp. 229)

When arguing that investors are affected by exogenous factors in their trading behaviour, naturally more than just pollution levels may have an impact, e.g. their general health and wellbeing.

Furthermore, other factors, which will not be studied in this project, may have an influence on behaviour such as investor demographics in terms of age, geographical location, family, educational level and others. It could also be external factors like traffic annoyance and workload or potential sector specific news that infer changes to an entire sector.

When studying which factors affect behaviour it is arguably a combination of a very large field of exposures. It is not possible to account for all of them, and some may even be impossible to measure. It would require a high degree of microdata and knowledge of traders, which is not accessible and within the scope of this project.

4.4.4 Strengths and Weaknesses in the Approach

The OLS regression was chosen as the methodological approach due to assumed linearity in data. This method does not require a significantly large dataset in order to conduct an analysis. Further it is straightforward in both setup and interpretation. A setback to the method is that it is highly sensitive to outliers. If data ultimately is not linear, the approach will do poorly in explaining data.

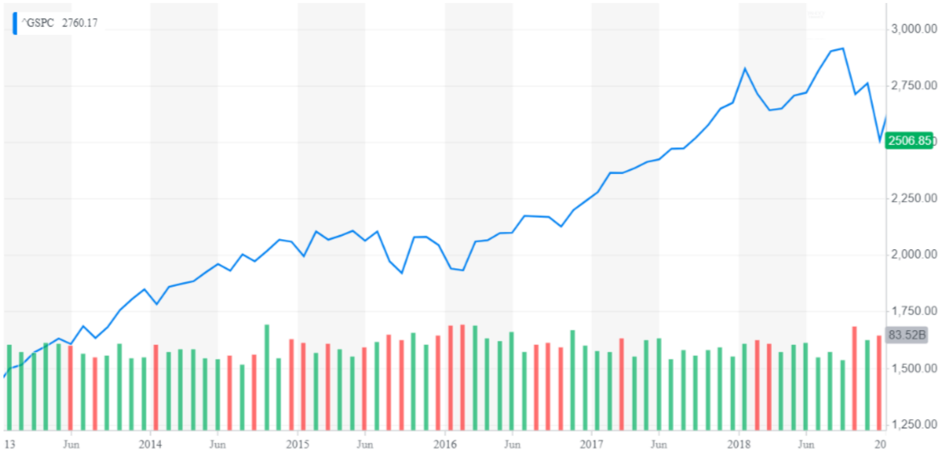
4.5 Economic Setting

This section will briefly introduce the main characteristics and events of the observed time period in the economic landscape, with a special focus on the US due to the data foundation. Thereby, providing an understanding of the financial environment this study is conducted in, to help discover some potential biases within the data.

4.5.1 Years of Bulls

The last ten years have had positive returns on the economic scene. For the time period of this paper (2013-2019), the market shown through the S&P 500 index has gone up consistently, apart from downturns in mid-2015, the beginning of 2016 and December 2018 (Figure 7).

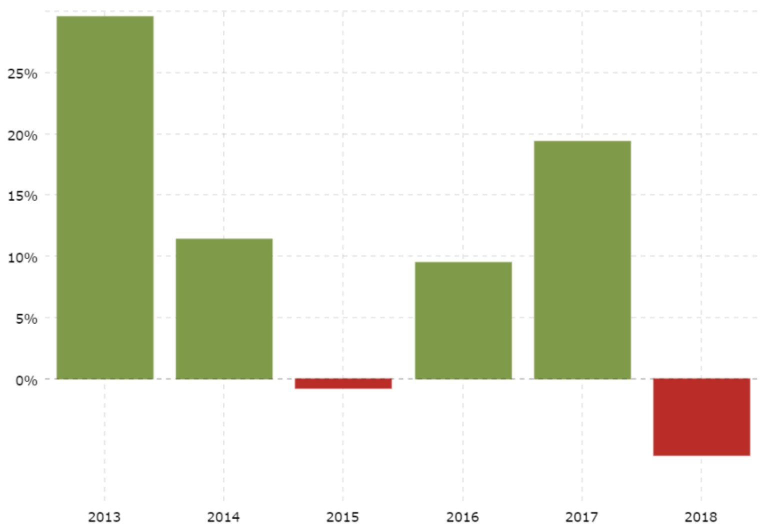
Figure 7 - Chart of S&P 500 Index in the Period from January 1st, 2013 Through January 1st, 2019



Source: Yahoo Finance, 2019

However, December 2018 turned out to be a bear market inside the bull partly due to anticipation of announcement from the Federal Reserve in the US and fear of an upcoming recession (Li, 2019).

Figure 8 - Annual Percentage Returns Calculated at Return Last Day of the Year Compared with Year Before. Illustrated Through S&P 500



Source: Macrotrends, 2019

The above graph (Figure 8) shows that the return in 2013 compared to 2012 on S&P 500 was 29.60 percent and 11.39 percent in 2014. In 2015 there was a minor negative return of 0.73 percent. Returns in 2016 and 2017 were positive with 9.54 percent and 19.42 percent respectively. 2018 presented the lowest returns of the time period in question with a negative 6.24 percent.

4.5.2 Zero-Interest Environment

Zero interest, and negative interest in real terms should, in theory, shift investments from the bond market to the equity market, making equities more attractive. It is a political way of attempting to decrease individuals' savings rate and increase the attractiveness of borrowing, hereby boosting the economy. (The Economist, 2013)

The environment might however not only have a positive effect on the equity market. A political decrease in the interest rates may also reflect a state of anxiety for a new financial downturn, which in turn may stop individuals from lending and investing. This would thereby not create an attractive market for equities. Therefore, the effect of the zero-interest environment naturally influences the stock market but cannot conclusively be decided in which direction the effect is strongest.

4.5.3 Geopolitical setting

Trade war between the United States and China has sent the world economy into a turbulence, where announcements from both sides lead markets into negative figures. Sanctions and tariffs to and from China will affect the US economy greatly. Hence, too, the largest companies in the country that are dependent on China as a supplier, buyer and trading partner. Essential imports from China include car parts and circuit boards among a wide range of industrial components. (The Economist, 2019a)

Estimations show that a 25 percent tariff could result in inflation in the United States with as much as half a percentage point. Furthermore, President Donald Trump has announced the introduction of 25 percent tariffs on import not yet affected, which has been estimated at a value of $300 billion (The Economist, 2019a). According to the Economist, the thing that creates the most turmoil is not the tariffs themselves however, but rather the uncertainty the trade war brings. (The Economist, 2019b)

Thus, the dataset for this paper has a strong correlation with developments in the trade war, and announcements from either sides along with rising uncertainty, which in turn can affect the daily data collected.

4.5.4 Conclusion

Preceding arguments would indicate that the stock market over the defined time period has positive returns. However, the trade war may have caused friction in the markets, making the future less certain and thereby making investments in American companies less attractive. There is an awareness that the points previously mentioned weigh heavily in the dataset of this thesis.

4.6 Hypothesis I

This section will explain the main assumptions made, on which the later analysis has been built. Some of the assumptions will be repeated in multiple hypotheses and will thus only be explained once.

4.6.1 Assumptions

All weather variables as well as Monday and January are control variables included to seek out as accurate an effect of $PM_{2.5}$ as possible. Thus, the main independent variable of the regression is the air pollution variable, $PM_{2.5}$. A key assumption made in this context is, that it is assumed that $PM_{2.5}$ and the error term ε_t are independent. When assuming an independent error term, the effects that are not possible to include meaningfully within the regression, lies in the error term.

For example, this paper studies only the local effects of air pollution and thus does not take into account that most trading today is done digitally. Therefore, investors investing on the NYSE could be located outside the city, or even outside the state.

Secondly, this regression measures ambient air pollution using $PM_{2.5}$ as a proxy, since this is identified as the most harmful to human health. In reality, more ambient air pollutants affect human physical and mental health, thus also their decision-making. Hence, this project builds on the assumption that $PM_{2.5}$ represents the main effects on human decision-making resulting from air pollution exposure.

4.6.2 Summary Statistics

Below in Table 1 a descriptive statistic of all included variables in Hypothesis I is presented. The table shows for all variables the number of observations (nbr.val), number of nulls (nbr.null), number of N/A (nbr.na), the minimum (min), maximum (max) and range (range) of the variable, the sum (sum), median (median), mean (mean), mean of standard deviation (SE.mean), mean of the 95 percent confidence interval (CI.mean.0.95), variance (var), standard deviation (std.dev) and finally the variance of the coefficient (coef.var).

Table 1 - Summary Statistics for Hypothesis I

	Log Daily Return	PM2.5	Temperature	Dew Point	Air Pressure	Visibility	Wind Speed
nbr.val	1258.0000	1258.0000	1258.0000	1258.0000	1258.0000	1258.0000	1258.0000
nbr.null	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
nbr.na	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
min	-0.0395	1.5664	10.9000	-8.0000	989.8000	1.1000	2.5000
max	0.0440	30.6000	90.9000	74.1000	1039.5000	10.0000	22.5000
range	0.0835	29.0336	80.0000	82.1000	49.7000	8.9000	20.0000
sum	-0.0863	11917.2401	71750.6000	53189.7000	1277713.2000	11725.4000	11677.3000
median	-0.0003	8.6167	58.2500	44.0000	1015.5000	10.0000	8.7000
mean	-0.0001	9.4732	57.0355	42.2812	1015.6703	9.3207	9.2824
SE.mean	0.0002	0.1095	0.5020	0.5336	0.2040	0.0397	0.0944
CI.mean.0.95	0.0004	0.2148	0.9848	1.0468	0.4002	0.0778	0.1852
var	0.0001	15.0818	317.0080	358.1828	52.3521	1.9808	11.2139
std.dev	0.0080	3.8835	17.8047	18.9257	7.2355	1.4074	3.3487
coef.var	-116.9653	0.4100	0.3122	0.4476	0.0071	0.1510	0.3608

	Snow Depth	Fog Dummy	Haze Dummy	January Dummy	Monday Dummy	Precipitation
nbr.val	1258.0000	1258.0000	1258.0000	1258.0000	1258.0000	1258.0000
nbr.null	1139.0000	911.0000	1078.0000	1156.0000	1023.0000	779.0000
nbr.na	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
max	15.0000	1.0000	1.0000	1.0000	1.0000	4.8800
range	15.0000	1.0000	1.0000	1.0000	1.0000	4.8800
sum	483.7000	347.0000	180.0000	102.0000	235.0000	154.9600
median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
mean	0.3845	0.2758	0.1431	0.0811	0.1868	0.1232
SE.mean	0.0422	0.0126	0.0099	0.0077	0.0110	0.0090
CI.mean.0.95	0.0828	0.0247	0.0194	0.0151	0.0216	0.0176
var	2.2410	0.1999	0.1227	0.0746	0.1520	0.1014
std.dev	1.4970	0.4471	0.3503	0.2731	0.3899	0.3184
coef.var	3.8933	1.6209	2.4482	3.3678	2.0873	2.5850

4.7 Hypothesis II

4.7.1 Assumptions

Main assumptions of the second hypothesis built on the conclusions from the first hypothesis. Hence, assuming that the results of weather control variables, will show the same trend when introducing ESG scores. For this reason, they have been excluded from Hypothesis II, III and IV and are not tested any further. Accordingly, Hypothesis II primarily focuses on the connection between stock market return, trade activity and pollution data, when introducing ESG scores.

It is assumed, that investors choose to invest in companies based on ESG scores. Although other factors, outside the scope of this research, may contribute to the investment decisions. The arguably large dataset measured on number of firms and their similarities as S&P 500 companies, secure that at least a part of the investment decision can be contributed to the ESG score.

Where Hypothesis I assumed that investors only look at the expected return when affected by pollution, Hypothesis II further expands this assumption, looking at the companies' sustainability features and transparency. Hence, the assumption builds in an extra dimension of the investment decision to also include nonfinancial company data.

4.7.2 Portfolio Construction

To test the second hypothesis of the study, portfolios based on the companies' overall ESG score have been constructed (Table 2). The average ESG score of all studied firms in the entire period from 2013 through 2018 is 48.33 and the median is 44.19.

Table 2 - Average and Median ESG Scores

	2013	2014	2015	2016	2017	2018	Overall
Average	48.4069	50.2524	52.2350	53.6997	54.7628	30.6103	48.3279
Median	46.2154	48.7742	51.3216	53.1386	54.4701	26.3764	44.1889

The portfolios will be divided into 'high scoring' and 'low scoring', with the median being the divisional point for each year. This ensures a reasonable distribution of firms in each category for each year. It should also be noted that most of the scores are compared to a sector benchmark, which implicates that the scores are relative values and explain the overall performance within an industry.

The portfolios constructed will hereby divide the high and low scoring companies based on their scores, assuming investors see it as information across companies. Therefore, they do not compare within the same sector but compare to other firms based on ESG scores. Following this logic, higher scoring firms will also have higher returns and more trading activity than lower scoring firms, because outside investors see ESG information as knowledge about companies' overall health and performance. The second hypothesis therefore assumes that investors do not have preferences for certain sectors or industries, but merely look at the performance across sectors. Furthermore, the portfolios are equally weighted. This is due to the fact that all are present in the S&P 500 index, and therefore represent the largest US companies from different sectors. Since all share similar characteristics in the large cap section, and the focus will be on the corresponding ESG scores, all carry the same weights in the constructed portfolios.

4.7.3 Summary Statistics

Presented in Table 3 below is a descriptive statistic of all included variables in Hypothesis II. For a further explanation all descriptive measures are clarified above in 4.6.2.

Table 3 - Summary Statistics for Hypothesis II

	Average return	High ESG	Low ESG	High trade	Low trade	PM2.5
nbr.val	1509.0000	1509.0000	1509.0000	1.509000e+03	1.509000e+03	1509.0000
nbr.null	0.0000	0.0000	0.0000	0.000000e+00	0.000000e+00	62.0000
nbr.na	0.0000	0.0000	0.0000	0.000000e+00	0.000000e+00	0.0000
min	-0.0266	39.4152	22.3778	1.897185e+06	9.935513e+05	-0.3737
max	0.0275	68.4819	40.8260	1.355391e+07	7.385921e+06	30.6000
range	0.0541	29.0666	18.4482	1.165672e+07	6.392370e+06	30.9737
sum	0.4436	92975.2454	52201.9279	9.165530e+09	4.461342e+09	13588.2251
median	0.0005	66.6081	37.2643	5.834271e+06	2.827968e+06	8.3167
mean	0.0003	61.6138	34.5937	6.073910e+06	2.956489e+06	9.0048
SE.mean	0.0001	0.2595	0.1556	3.519005e+04	1.856563e+04	0.1122
CI.mean.0.95	0.0003	0.5091	0.3052	6.902664e+04	3.641720e+04	0.2200
var	0.0000	101.6532	36.5270	1.868655e+12	5.201261e+11	18.9893
std.dev	0.0052	10.0823	6.0438	1.366988e+06	7.211977e+05	4.3577
coef.var	17.7210	0.1636	0.1747	2.251000e-01	2.439000e-01	0.4839

4.8 Hypothesis III

4.8.1 Assumptions

Hypothesis III further extends Hypothesis II by analysing each component; E, S and G. It is in this part of the analysis assumed that each component plays a different role in the investment decision, where the score of one component may weigh more heavily than the score of another component. Hence, the assumption of this analysis is not only that investors look at nonfinancial data in the investment decision, but that they also evaluate each component of the ESG score and potentially weigh them differently.

This hypothesis particularly plays into the later mentioned greenwashing, the effects of media and the investor's general environment. Although all three components can be considered crucial company information, either from an investment or ethical point of view, the focus of the surroundings may in some sense dictate the focal point of sustainable investing.

4.8.2 Portfolio Construction

Identical methodology from Hypothesis II is used studying the third hypothesis. The portfolios are constructed based on environmental (Table 4), social (Table 5) and governance (Table 6) scores respectively. The median and the average from each parameter can be seen for each year below. The median will divide the portfolios in low and high performing.

Table 4 - Median and Average of Environmental Score

Environmental	2013	2014	2015	2016	2017	2018
Median	16.1859	20.8578	25.0000	29.6681	28.6205	0.0000
Average	27.0663	29.3728	31.0241	32.8836	33.2205	4.2112

Table 5 - Median and Average of Social Score

Social	2013	2014	2015	2016	2017	2018
Median	41.6427	45.4734	47.0291	50.0000	50.0000	0.0000
Average	41.2170	44.8612	47.8634	50.0414	51.9150	16.3688

Table 6 - Median and Average of Governance Score

Governance	2013	2014	2015	2016	2017	2018
Median	75.2515	76.0135	76.4368	77.1307	77.9783	75.7361
Average	71.4058	72.8027	74.0408	75.2324	76.4464	71.2662

As the above tables show there are rather large differences in the median across the three different ESG parameters. For 2013 governance is arguably high with 75.2515 as the median, the social parameter follows with 41.6427 and environmental has a median of only 16.1859. The same trend can be observed for the remaining years. It should be noted that the large differences between the three parameters could be due to the different number of metrics included in calculating each parameter. Governance includes 37 different metrices, whereas social has eight and environmental only consists of three. The more different aspects are included in the parameter, the easier it is to achieve a higher score for the concerned parameter. This could explain why governance consistently show the highest median and average.

4.8.3 Summary Statistics

The summary statistics depicted below in Table 7 presents all included variables in the analysis of Hypothesis III. A more detailed description of the statistical measures can be found above in 4.6.2.

Table 7 - Summary Statistics for Hypothesis III

	Average return	Average E score	Average S score	Average G score	Average E trade
nbr.val	1510.0000	1510.0000	1510.0000	1510.0000	1.510000e+03
nbr.null	0.0000	0.0000	0.0000	0.0000	0.000000e+00
nbr.na	0.0000	0.0000	0.0000	0.0000	0.000000e+00
min	-0.0264	23.2805	23.1019	71.6195	1.440653e+06
max	0.0285	33.2788	52.5082	77.0023	1.182070e+07
range	0.0549	9.9983	29.4063	5.3828	1.038005e+07
sum	0.4468	44785.7595	65190.6272	111918.1053	6.885131e+09
median	0.0005	30.4315	46.6580	74.0661	4.414297e+06
mean	0.0003	29.6594	43.1726	74.1180	4.559690e+06
SE.mean	0.0001	0.0892	0.2565	0.0473	2.647711e+04
CI.mean.0.95	0.0003	0.1749	0.5031	0.0928	5.193584e+04
var	0.0000	12.0014	99.3338	3.3787	1.058566e+12
std.dev	0.0052	3.4643	9.9666	1.8381	1.028867e+06
coef.var	17.6495	0.1168	0.2309	0.0248	2.256000e-01

	Average S trade	Average G trade	PM2.5
nbr.val	1.510000e+03	1.510000e+03	1510.0000
nbr.null	0.000000e+00	0.000000e+00	62.0000
nbr.na	0.000000e+00	0.000000e+00	0.0000
min	1.447579e+06	1.456053e+06	-0.3737
max	1.013791e+07	1.019983e+07	30.6000
range	8.690328e+06	8.743778e+06	30.9737
sum	6.830504e+09	6.781269e+09	13598.1920
median	4.370486e+06	4.361240e+06	8.3271
mean	4.523512e+06	4.490907e+06	9.0054
SE.mean	2.566222e+04	2.506273e+04	0.1121
CI.mean.0.95	5.033740e+04	4.916149e+04	0.2199
var	9.944097e+11	9.484923e+11	18.9773
std.dev	9.972009e+05	9.739057e+05	4.3563
coef.var	2.204000e-01	2.169000e-01	0.4837

4.9 Hypothesis IV

4.9.1 Assumptions

It is reasonable to think that there may be a significant difference between low and high scoring companies within each sector. Investors might often have a field of expertise, where they naturally invest more heavily. If the assumption that the investor has already chosen to invest within a certain sector holds, does the ESG score then play a role in choosing which company to invest in?

The last part of the analysis therefore assume that investors will have a predetermined sector which they invest in and, given that sector, choose between companies within this sector. Thus, this project creates and tests a high and a low scoring portfolio within each sector.

Because some of the sectors have relatively few companies represented, the results of the better represented sectors will contribute more greatly to the conclusions of this part.

Additionally, it could be assumed that some sectors may experience higher trade activity, and possibly higher returns, on days with high pollutions, because investors decide to invest in less polluting sectors or industries. Thus, there might be a shift in company trade activity depending on the level of pollution that particular day.

4.9.2 Portfolio Constructions

For the final hypothesis, 20 portfolios will be constructed. Each portfolio will contain either low ESG scoring companies or high ESG scoring companies within each of the ten studied sectors. Since each sector has different averages and medians of ESG scores for the companies, the low and high portfolios will be divided based on the median within each sector. Below tables (Table 8 and Table 9) show both the medians and averages of the ESG scores for each industry for the individual years.

Table 8 - Median and Average of Sectors for 2013-2018 (Part 1)

	2013		2014		2015	
	Median	**Average**	**Median**	**Average**	**Median**	**Average**
Communications	35.49	36.93	37.05	40.71	38.64	42.03
Consumer Discretionary	37.03	41.84	41.23	45.21	44.44	46.36

Consumer Staples	56.66	54.09	60.31	55.32	60.25	56.68
Energy	50.04	50.25	46.96	50.62	49.71	52.38
Financials	39.92	43.96	41.18	47.48	41.70	49.25
Healthcare	40.12	46.33	41.49	47.70	43.89	50.93
Industrials	45.68	45.47	46.36	46.70	50.91	48.94
Materials	58.62	54.38	59.79	56.57	59.98	57.67
Technology	43.06	49.48	44.89	52.22	55.77	54.94
Utilities	57.75	54.17	58.88	56.79	59.48	59.01

Table 9 - Median and Average of Sectors for 2013-2018 (Part 2)

	2016		**2017**		**2018**	
	Median	**Average**	**Median**	**Average**	**Median**	**Average**
Communications	39.39	42.91	39.20	42.37	23.58	28.75
Consumer Discretionary	49.02	48.74	45.75	48.73	28.16	32.35
Consumer Staples	63.12	59.85	63.00	60.00	40.35	39.41
Energy	54.55	53.63	53.01	55.91	25.30	27.45
Financials	42.21	51.10	44.86	53.66	26.22	26.48
Healthcare	45.59	52.99	51.29	54.26	26.10	30.61
Industrials	49.07	50.66	53.04	51.89	25.93	28.14
Materials	60.85	57.71	62.91	60.15	24.38	24.02
Technology	57.31	56.51	57.13	56.30	39.33	39.60
Utilities	61.37	59.19	61.97	60.00	25.38	26.13

For some sectors, the difference between the median and the average is noticeable, for example for financials, indicating a skewness of scores. Consumer stables, energy and utilities are sectors that show consistently high levels of ESG scores, whereas communication has performed the worst across the time period.

As each sector has a different amount of companies represented in the data, some regressional results may weigh more heavily in the conclusions and discussion than other sectors. This matter will be discussed later in the project.

4.9.3 Summary Statistics

As shown in the table below (Table 10), a summary of all the variables included as well as the descriptive statistics here have been presented. In 4.6.2 an in-depth explanation of the included measures has been presented.

Table 10 - Summary Statistics for Hypothesis IV

	Com ESG	CD ESG	CS ESG	Fin ESG	Nrg ESG	HC ESG	Indu ESG	Mat ESG
nbr.val	1510.0000	1510.0000	1510.0000	1510.0000	1510.0000	1510.0000	1510.0000	1510.0000
nbr.null	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
nbr.na	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
min	29.8538	33.7407	40.5169	26.5633	27.1163	30.6722	28.3280	24.1049
max	45.3802	48.8361	60.8586	54.2282	55.8006	54.2570	51.6611	59.9217
range	15.5264	15.0954	20.3416	27.6649	28.6843	23.5847	23.3331	35.8169
sum	62266.1232	66621.0297	82810.0292	69104.5682	73114.9660	71510.9008	68936.1056	78110.4830
median	43.4620	45.7671	56.5423	48.7607	51.7082	49.4049	48.5030	57.0863
mean	41.2358	44.1199	54.8411	45.7646	48.4205	47.3582	45.6531	51.7288
SE.mean	0.1404	0.1326	0.1754	0.2336	0.2485	0.2026	0.2057	0.3215
CI.mean.0.95	0.2755	0.2601	0.3440	0.4582	0.4875	0.3974	0.4034	0.6305
var	29.7806	26.5546	46.4401	82.3799	93.2783	61.9875	63.8781	156.0300
std.dev	5.4572	5.1531	6.8147	9.0763	9.6581	7.8732	7.9924	12.4912
coef.var	0.1323	0.1168	0.1243	0.1983	0.1995	0.1662	0.1751	0.2415

	Tech ESG	Uti ESG	Com trade	CD trade	CS trade	Fin trade	Nrg trade
nbr.val	1510.0000	1510.0000	1.510000e+03	1.510000e+03	1.510000e+03	1.510000e+03	1.510000e+03
nbr.null	0.0000	0.0000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
nbr.na	0.0000	0.0000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
min	39.3436	26.6667	2.469949e+06	1.140606e+06	1.049138e+06	9.862929e+05	1.392509e+06
max	57.3069	62.4224	2.219626e+08	8.054257e+06	1.326633e+07	1.139496e+07	1.674270e+07
range	17.9634	35.7557	2.194927e+08	6.913650e+06	1.221720e+07	1.040867e+07	1.535019e+07
sum	78659.6881	82107.5536	3.017899e+10	5.897393e+09	6.215802e+09	6.217238e+09	8.015704e+09
median	54.2678	59.8980	8.479661e+06	3.771989e+06	3.962429e+06	3.881563e+06	4.920518e+06
mean	52.0925	54.3759	1.998609e+07	3.905558e+06	4.116425e+06	4.117376e+06	5.308413e+06
SE.mean	0.1567	0.3234	7.104302e+05	2.222183e+04	2.624338e+04	3.144812e+04	4.491398e+04
CI.mean.0.95	0.3074	0.6343	1.393535e+06	4.358895e+04	5.147736e+04	6.168666e+04	8.810045e+04
var	37.0919	157.9082	7.621137e+14	7.456527e+11	1.039959e+12	1.493366e+12	3.046071e+12
std.dev	6.0903	12.5662	2.760641e+07	8.635118e+05	1.019784e+06	1.222034e+06	1.745300e+06
coef.var	0.1169	0.2311	1.381300e+00	2.211000e-01	2.477000e-01	2.968000e-01	3.288000e-01

	HC trade	Indu trade	Mat trade	Tech trade	Uti trade	PM2.5
nbr.val	1.510000e+03	1.510000e+03	1.510000e+03	1.510000e+03	1.510000e+03	1510.0000
nbr.null	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	62.0000
nbr.na	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.0000
min	8.935442e+05	9.970055e+05	1.137997e+06	2.013798e+06	8.467483e+05	-0.3737
max	9.597999e+06	1.122038e+07	1.149262e+07	1.621282e+07	8.205806e+06	30.6000
range	8.704455e+06	1.022338e+07	1.035462e+07	1.419902e+07	7.359058e+06	30.9737
sum	5.099685e+09	4.705833e+09	5.721316e+09	1.054903e+10	4.346406e+09	13598.1920
median	3.218983e+06	2.865389e+06	3.487105e+06	6.628355e+06	2.744380e+06	8.3271
mean	3.377275e+06	3.116445e+06	3.788951e+06	6.986109e+06	2.878415e+06	9.0054
SE.mean	2.359745e+04	2.785086e+04	3.475334e+04	4.879202e+04	1.960632e+04	0.1121
CI.mean.0.95	4.628728e+04	5.463051e+04	6.816997e+04	9.570737e+04	3.845854e+04	0.2199
var	8.408278e+11	1.171263e+12	1.823770e+12	3.594799e+12	5.804560e+11	18.9773
std.dev	9.169667e+05	1.082249e+06	1.350470e+06	1.895995e+06	7.618766e+05	4.3563
coef.var	2.715000e-01	3.473000e-01	3.564000e-01	2.714000e-01	2.647000e-01	0.4837

4.10 Limitations

Following, a brief presentation and discussion of project limitations regarding data, studied time period and possible conclusions.

4.10.1 Why New York?

New York City has been the city chosen to investigate, both due to availability of extensive weather and pollution data. Also, since US is one of the largest economies in the world and New York City is considered an international trading hub. Furthermore, large amounts of the studied companies have their headquarters in the city, potentially creating a home bias for investors that would be relevant for the study. Lastly, New York City is a large city, which will have a dense population and pollution.

4.10.2 Time period

The time period was chosen based on available ESG information. Hence, this research is limited by data available, since sustainable scores are a rather new area of data, but also limited of the scope of the dataset since it is based on daily basis.

Although the time period is inarguably short, data will be analysed on a daily basis for weekdays through all six years. Hereby, the dataset consists of more than 1,200 observations and arguably an acceptable amount for this type of study. Since the four hypotheses demand different portfolio constructions, with different portfolios each year the time consumption of including more years would have been larger than the scope of this paper.

The awareness of the limitations that follow such a narrow annual timeframe and that certain political or financial events create the possibility of a distortion of data, are taken into consideration. Having data on a daily basis with lags does however partly make up for this.

4.10.3 Weekdays

Since the financial markets are only open on weekdays, it is not possible to attain trading information neither Saturday nor Sunday. As this is the case for trading data, pollution data has been matched to also not include weekends. This causes Monday data lagged one period will be data collected on Friday. While this thesis primarily focuses on the immediate effects of air pollution, this exclusion of weekends is not considered a hindrance for valid conclusions.

4.10.4 NYSE, S&P 500 & ESG Scores

Hypothesis I study the NYSE Composite Index, which includes more than 1,900 companies. This is thereby the broadest way to study the American market and is used to establish the connection between air pollution and stock market returns. Due to the limited scope of this thesis, it was not possible to study ESG data on from such a large number of companies. Therefore, S&P 500 was chosen to further develop the analysis.

S&P 500 has been chosen because it includes some of the largest American companies, making their stocks frequently traded and less volatile than small- or mid-cap companies. The size of the companies also ensures that sufficient amount of data of sustainability is disclosed, resulting in the majority of companies having an ESG score higher than zero.

Because some companies do have a score of zero, a liquid limit rather than a rigid one, the yearly median, was chosen in the creation of the high and low ESG portfolios. Especially during 2018 many companies had a score of zero, skewing results drastically. Furthermore, for some years the same was true for the individual E, S and G scores.

4.10.5 Sectors not Industries

Whereas similar studies have focused on certain industries, this study chose to focus on sectors. Sector is a wider term and contains several industries within. Since this study analyses S&P 500 and the amount of different industries within this index is large, sectors instead of industries were chosen. For example, the consumer stables sector is made up of six different industries; beverages, food & staples retailing, food products, household products, personal products and the tobacco industry. (Kennon, 2019)

As a study of the more sinful industries, such as tobacco, would require more companies than is represented on the S&P 500, it is outside the scope of this project. This study view sectors on an overall basis and compares the companies within based on their ESG score.

4.10.6 Understanding Behaviour

As discussed in a previous section, pollution has both a physical and a psychological effect on humans. These effects can be small or larger changes in behaviour which the investor might not be conscious about. This thesis is unable to determine whether changes in investment behaviour caused by pollution is driven by a conscious or unconscious choice. As New York City's pollution level has drastically decreased over the past decades, daily warning messages are not likely to be sent out anymore, making it an active decision if one wants to discover the day's pollution levels. One thing is what is actual pollution, another one is what people perceive. For this reason, it is relevant to analyse fog levels, as they might easily be confused with actual air pollution.

4.10.7 Who is Investing?

It is not possible to obtain investor information for the studied companies in the studied time period, leaving the question of: Who is investing? This thesis concerns itself with individual investors, which make individual decisions regarding their investments. Therefore, this study does not wish to examine institutional investors, where the process of investing would imply a high degree of sparring between several people, perhaps reducing the effect induced by air pollution. However, it is not possible to distinguish between individual or institutional investors, which may influence the obtained results.

5 Data Description

The following section displays and describes the acquisition and origin of the data on which the empirical analysis has been based. Time series data on market's daily returns have been gathered from the New York Stock Exchange (NYSE) based on adjusted closing price. Additionally, five weather variables, acting as mood-proxy variables, an air pollution variable ($PM_{2.5}$) as well as two market anomaly control variables have been used to explain the effect of air pollution on daily returns. All included variables are displayed below in Table 11, and origin and treatment described further in the following sections.

Table 11 - Explanation of Variables

Name	Type	Unit of Measure
Panel A		
Daily Log Return, r_t	ln(adj. closing$_t$)−ln(adj. closing$_{t-1}$)	Index
$PM_{2.5}$	24-hour average	Micrograms/cubic meter
Temperature, T_t	Daily average	Degrees Fahrenheit
Dew Point, DP_t	Daily average	Degrees Fahrenheit
Air Pressure, AP_t	Daily average	Millibars
Visibility, V_t	Daily average	Miles
Wind Speed, WS_t	Daily average	Knots
Precipitation, P_t	Total daily	Inches
Snow Depth, SD_t	Total daily	Inches
Fog, F	Dummy variable	1 = Fog, 0 = Otherwise
Haze, H	Dummy variable	1 = Haze, 0 = Otherwise
January, J	Dummy variable	1 = January, 0 = Otherwise
Monday, M	Dummy variable	1 = Monday, 0 = Otherwise
Panel B		
Average daily return, r_t	Daily average	Percent
ESG High, ESG_t^H	Yearly measure	Score from median for year-100
ESG Low, ESG_t^L	Yearly measure	Score from 0-median for year
Trade volume, v_t^H	Daily average	Variable based on ESG High
Trade volume, v_t^L	Daily average	Variable based on ESG High
$PM_{2.5, t-2}$	24-hour average 2-days lags	Micrograms/cubic meter
Panel C		

Average daily return, r_t	Daily average	Percent
E Score, E_t	Yearly measure	Score from 0-100
S Score, S_t	Yearly measure	Score from 0-100
G Score, G_t	Yearly measure	Score from 0-100
Trade volume, v_t^E	Daily average	Average of trade
Trade volume, v_t^S	Daily average	Average of trade
Trade volume, v_t^G	Daily average	Average of trade
$PM_{2.5,\, t-2}$	24-hour average 2-days lags	Micrograms/cubic meter
Panel D		
Average daily return, r_t	Daily average	Percent
$PM_{2.5,\, t-2}$	24-hour average 2-days lags	Micrograms/cubic meter
ESG Score: Communications, ESG_t^{com}	Yearly measure	Score from 0-100
ESG Score: Consumer discretionary, ESG_t^{cd}	Yearly measure	Score from 0-100
ESG Score: Consumer staples, ESG_t^{CS}	Yearly measure	Score from 0-100
ESG Score: Energy, ESG_t^{nrg}	Yearly measure	Score from 0-100
ESG Score: Financial, ESG_t^{fin}	Yearly measure	Score from 0-100
ESG Score: Health Care, ESG_t^{HC}	Yearly measure	Score from 0-100
ESG Score: Industrials, ESG_t^{ind}	Yearly measure	Score from 0-100
ESG Score: Materials, ESG_t^{mat}	Yearly measure	Score from 0-100
ESG Score: Technology, ESG_t^{tech}	Yearly measure	Score from 0-100
ESG Score: Utility, ESG_t^{uti}	Yearly measure	Score from 0-100
Trade volume: Communications, v_t^{com}	Daily average	Number of stocks
Trade volume: Consumer discretionary, v_t^{cd}	Daily average	Number of stocks

Trade volume: Consumer staples, v_t^{CS}	Daily average	Number of stocks
Trade volume: Energy, v_t^{nrg}	Daily average	Number of stocks
Trade volume: Financial, v_t^{fin}	Daily average	Number of stocks
Trade volume: Health care, v_t^{HC}	Daily average	Number of stocks
Trade volume: Industrials, v_t^{ind}	Daily average	Number of stocks
Trade volume: Materials, v_t^{mat}	Daily average	Number of stocks
Trade volume: Technology, v_t^{tech}	Daily average	Number of stocks
Trade volume: Utility, v_t^{uti}	Daily average	Number of stocks

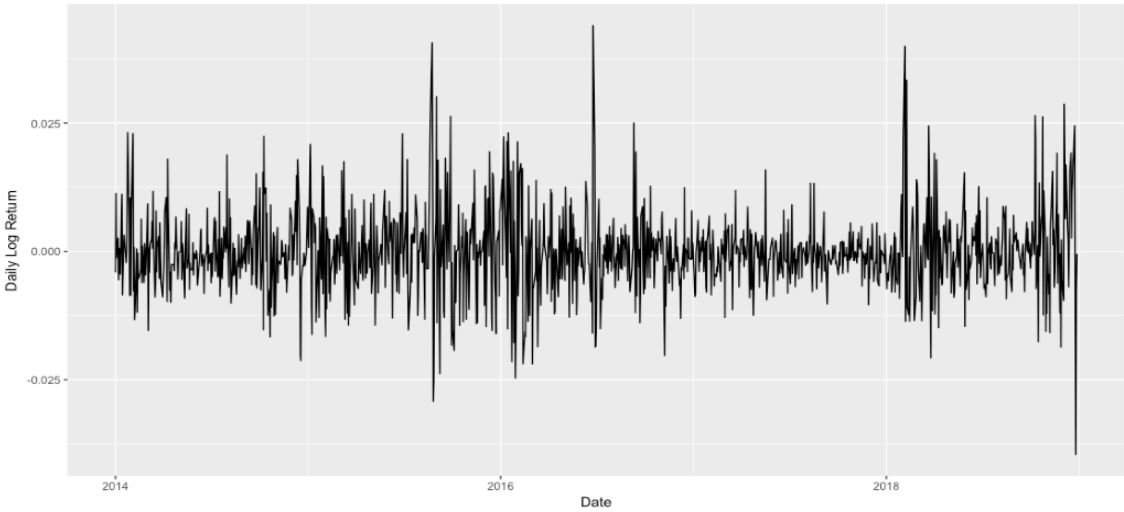
Panel A shows the variables presented in Hypothesis I with daily return from NYSE Composite Index, pollution given by $PM_{2.5}$ and all used weather control variables. Panel B presents the variables applied in Hypothesis II including daily return on S&P 500, high and low variables of the ESG score and trade volume as well as a score for the two-day lagged $PM_{2.5}$. Panel C shows variables for Hypothesis III including E, S & G scores, trade activity, daily returns and $PM_{2.5}$. Variables included in the last part of the analysis, Hypothesis IV, is shown in Panel D and includes all ten sectors' trade activity, average ESG score, average daily returns and $PM_{2.5}$.

5.1 Daily Returns

The main dependent variable of the conducted analysis of Hypothesis I is the daily stock market return on the New York Stock Exchange through the composite index. From the New York Stock Exchange data has been collected for all working days in the time period January 1st, 2014 through December 31st, 2018. For all dates the daily open, high, low, closing and adjusted closing prices have been collected. In calculating the daily stock returns, the log first difference between the adjusted closing price and the adjusted closing price of the previous trading day was applied. All stock market data has been obtained from Yahoo Finance.

Since daily returns are of a time series nature, it was necessary to analyse the stationarity of data, ensuring these did not contain any time trends. Initially a visual analysis was conducted, where Figure 9 shows the daily log return for the NYSE Composite Index during the studied period.

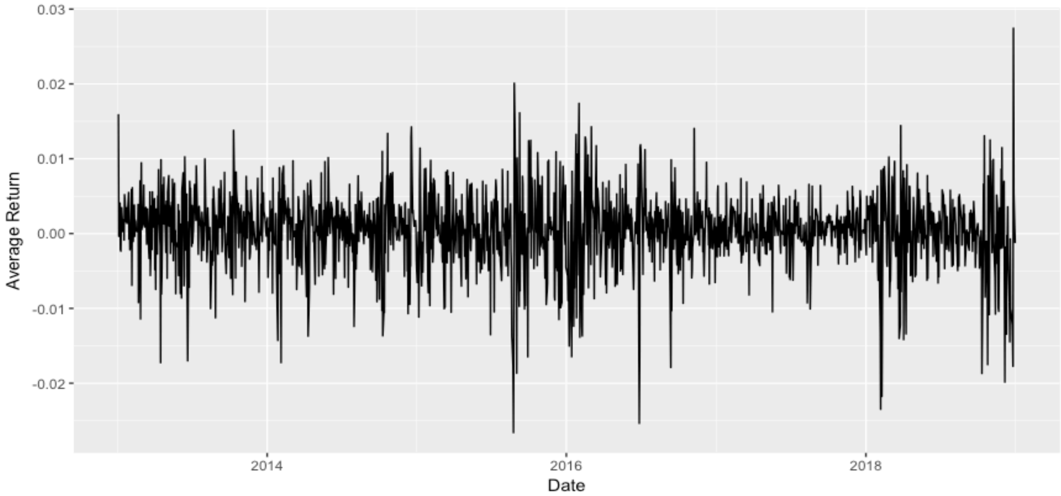
Figure 9 - Daily Log Return of NYSE from January 1st, 2014 through December 31st, 2018



Although the figure above shows no sign of any time trend and thus appears stationary, an augmented Dickey-Fuller test was conducted. The results hereof show how the null hypothesis of the presence of a unit root can be formally rejected with 99 percent certainty.

When testing Hypotheses II, III, and IV, the main dependent variable is an average daily stock market return, averaging daily adjusted closing prices of the 463 included companies during the period from January 1st, 2013 through December 31st, 2018. All data has been acquired through Yahoo Finance. As above, due to the nature of stock market returns, an analysis of the stationarity of data has been necessary. An identical approach as previously has been applied, firstly conducting a visual analysis shown in Figure 10.

Figure 10 - Average Daily Stock Return of Included Companies from January 1st, 2013 through December 31st, 2018



Again, visually there is no sign of the presence of a unit root, meaning the time series seem trendless. Yet, in order to be certain an augmented Dickey-Fuller test has been conducted. In doing so, it is possible to reject the presence of a unit root with 99 percent certainty.

5.2 Air Quality and Weather

As described in Nonfinancial Data and Stock Return, the literature reviewed established a clear connection between ambient air pollution and health/mood. Attempting to isolate the effect on daily stock market returns arisen from ambient air pollution, this thesis will control for a series of weather variables. This section elaborates on both pollution and weather data.

Air quality data is obtained through United States Environmental Protection Agency from their AQS Data Mart services. All over America monitors are placed, which measure an array of ambient air pollutants such as $PM_{2.5}$, PM_{10}, Ozon, Carbon Monoxide, Nitrogen Dioxide and others. Hourly data on $PM_{2.5}$ from the monitoring station placed at Division Street, New York, New York has been gathered for this project. This station was chosen as it is the one located in closest proximity to the NYSE, less than one mile, and thus is assumed to have the most precise results regarding the exposure on investors.

This thesis focuses on the effects of particulate matter $PM_{2.5}$, which is an air pollutant consisting of solid as well as liquid matter with a diameter of less than 2.5 micrometres. This pollutant is shown to be the most harmful air pollutant to human health. (WHO, Urban Health, 2019)

Daily values for air pollution are computed as a 24-hour average, in the time period from 00:00 to 23:59, resembling a full day. Calculating the daily average as the full 24-hour period was chosen as it is assumed there is daily fluctuations in emissions, fluctuating with rush-hours, night-time, lunch time and the like.

In trying to isolate the stock market effects arising from the air pollution affecting investors, this thesis is also controlling for and thus including weather factors. Literature has proven a correlation between weather variables and mood, including but not excluded to temperature, wind speed and visibility (Keller et al., 2005). In addition to weather influencing the mood, literature has also proven that weather can directly influence the stock market returns (Keef & Roush, 2007; Shu & Hung, 2009).

All weather data was obtained from the National Oceanic and Atmospheric Administration (NOAA) website, through their Global Summary of the Day (GSOD) database. Daily average temperature, dew point, air pressure, visibility, wind speed, precipitation and snow depth were extracted from the measuring station located at La Guardia Airport in New York. On the other hand, data regarding both the fog and the haze dummy variables were collected from the measuring station located in Lower Manhattan.

5.3 Other Controlled Variables

Other controlled variables include a dummy variable indicating Mondays and one indicating January. This is due to literature previously having proved that these influence stock market returns. Fama (1965), for example, shows in his study how the variance of the US stock market is significantly higher on Mondays, compared to the rest of the week. Authors such as Cross (1973) and French (1980) both investigate the effects of Mondays on stock market returns, finding that returns on Mondays are both negative and significant. In his studies investigating the Weekend effect, Rogalski (1984) also finds that Monday returns are negative from February through December. His study also shows that Monday returns are actually positive during January. This finding is supported by Ho (1990) who tested the Monday and the January effects on ten Asian Pacific markets. He finds that in the US, the average daily returns in January are significantly higher than the ones of the other months of the year at a five percent level.

The Monday and the January dummy variables have been made using Excel. The dates connected to the NYSE stock market returns was turned into month only and day only, from which the dummies where created. The Monday dummy will equal one when the trading day is a Monday and zero otherwise, where the January dummy will equal one if the trading day falls in January and zero otherwise.

5.4 ESG Data

Above, an increasing significance of nonfinancial data in decision-making has been established, but what could this nonfinancial information be? This section will explore ESG scores as a source of nonfinancial information relevant to investors.

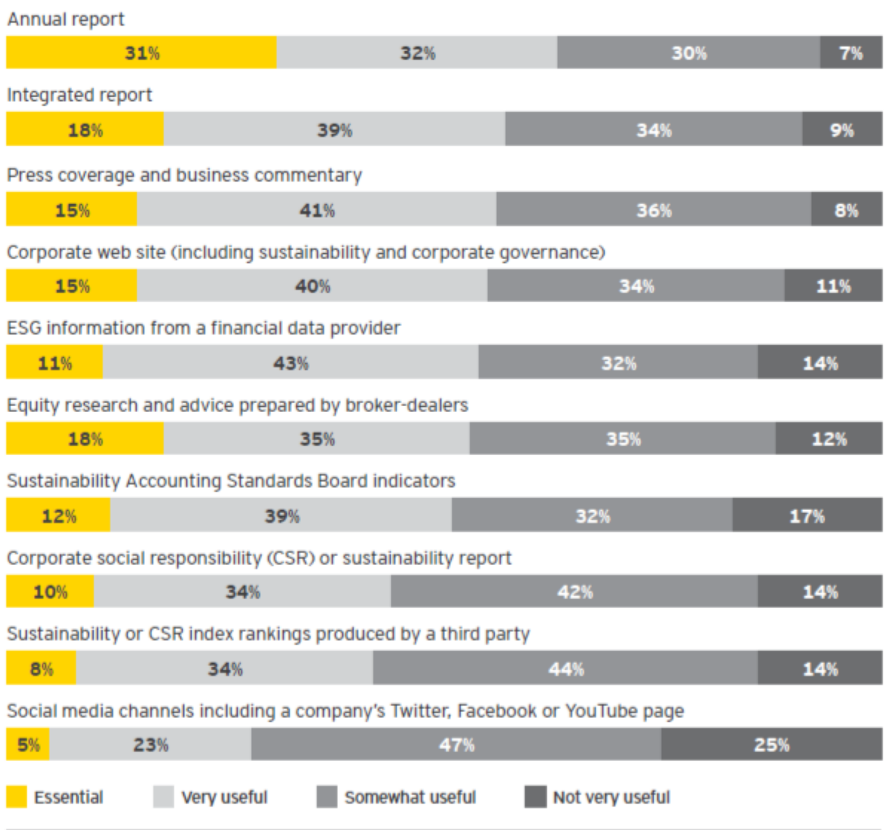
"In the past, the priority was always the governance side. Corporate governance — that was the area that had the most weight or relevance for investors. But in the last year, climate change has really accelerated, environmental risks have really gone up the agenda, and at the moment they seem to be of equal weight and importance in the discussion." Jennifer Anderson, Responsible Investment Office for London's Pension Trust (Ernest & Young, 2017, pp. 6)

The above quote by Jennifer Anderson would suggest that not only has nonfinancial data grown in significance to investors, but there has also been a shift in the particular focal points within this type of data. Increasing the awareness of environmental risk leads to an increased importance of environmental measures. This is because investors need a way to compare companies and determine which ones are the most attractive to invest in. One such measure is the ESG score, incorporating environmental, social and governance measures into a single score of 0 to 100. Ernest & Young (2017) further emphasises the relevance of the ESG score as a measure by stating how a rising population of millennials will amplify the importance of ESG factors in investing. This is due to them viewing ESG scores and sustainability differently than earlier generations. The same report has estimated a transfer of US $30 trillion from the earlier generations to the millennials, making them financially capable of influencing the investment scene in the future. This might lead to nonfinancial data growing in significance in the near future, as money is transferred from older generations to millennials, who might invest more sustainable.

Another reason, why investors find ESG scores to be valuable information when making a decision is related to the riskiness of the investment. The Head of ESG at AMP Capital, Adam Kirkman (Ernest & Young, 2017) explains further how "*ESG analysis provides investors with an additional lens for reviewing and evaluating companies and assets, not just for equity performance, but for factors that affect bond pricing and real asset valuations.*" (pp.4).

In 2017, Ernest & Young surveyed investors on nonfinancial information, how frequent nonfinancial data has played a pivotal role in decision-making (Figure 1) and what sources of nonfinancial data are the most useful (Figure 11).

Figure 11 - How Useful do You Find the Following Sources of Nonfinancial Information when Making an Investment Decision?



Source: Ernest & Young, 2017, pp. 18

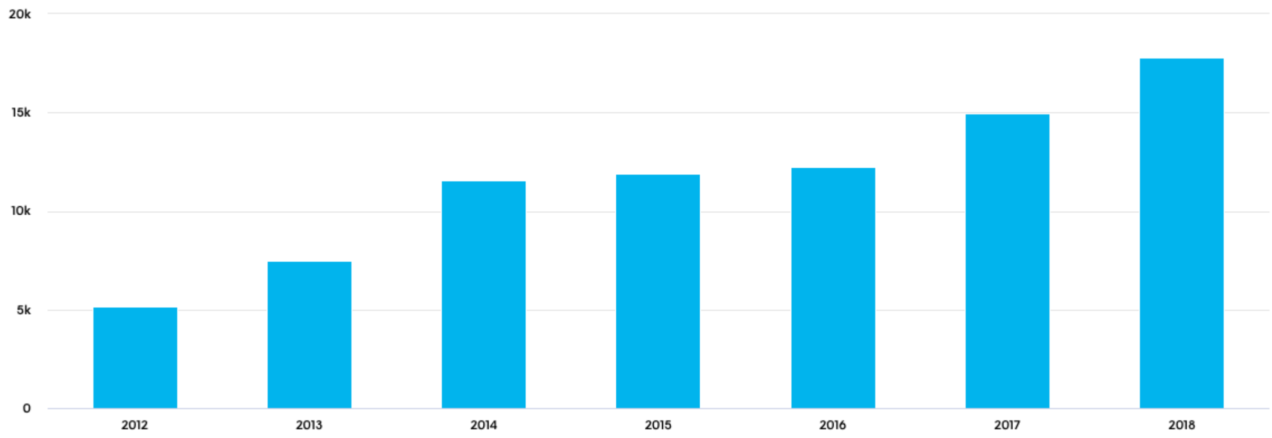
The survey showed that the annual report remains the most essential source of information, not only financial but also nonfinancial information. Also, the integrated report is essential to investors. This shows how official information provided by the company itself, revised by external professionals, is still the most trusted source of information. ESG information from a financial data provider, such as Bloomberg and Sustainalytics, was essential to 11 percent of the surveyed investors. 43 percent found it very useful and 32 percent somewhat useful, where only 14 percent of the investors rated it not very useful.

One drawback of the increased focus on environment and the creation of sustainability scores like ESG is greenwashing. Greenwashing occurs when a company through advertising claims to be green but does not spend the necessary time and money to initiate sustainable initiatives and minimise environmental impact (Edwards, 2018). Greenwashing is important to avoid, as the company should not only focus on the upside, but also the drawbacks of a more sustainable strategy and projects. They need to have concrete measures for the plans to materialize, otherwise it might be referred to as greenwashing. Therefore, transparency regarding information is of crucial importance, when scoring companies on their sustainability. Companies will benefit from disclosing as much information as possible, also in relation to the rest of their industry. Sustainability scores does not only draw information directly provided by the company itself, but also through news and other sources. Benefits lie in the truthfulness as scores will be higher and news better, thus providing the company with a higher status, making it more attractive to investors.

Another benefit of the ESG score compared to other sustainability matrixes is the comparability, across companies and sectors. Since it is not only dependent on the information the company publicly disclose themselves, it means that the ESG information is available for more than 11.000 companies on Bloomberg. (Bloomberg, 2019)

To measure the sustainability of firms, the thesis will use ESG scores provided by Bloomberg as proxies. As Figure 12 below depicts, Bloomberg has experienced almost exponential growth in the number of customers attaining ESG data through their terminals.

Figure 12 - The Number of Customers Using Bloomberg ESG Data



Source: Bloomberg, 2019

ESG scores are made of three components; environmental, social and governance. The scores are calculated based on all available information regarding the company within these three areas of interest. Thus, the ESG score is a measure of both sustainability and information transparency, meaning the more sustainable or the more a company discloses, the higher the ESG score it receives (Spitzer & Mandyck, 2019). Bloomberg uses several sources of information to calculate companies' ESG scores. Information included does not solely include company disclosed information, such as annual reports, but also news and other general pieces of public available information. This allows users to compare their score to peers from the same industry or the companies' own historical data to track potential development. Therefore, making the score dynamic and relative to industry levels.

There are several different sources providing publicly available ESG data. The most prevalent providers being Bloomberg, DataStream and Sustainalytics. This study utilises ESG data provided by Bloomberg with a focus on S&P 500. As mentioned, an ESG score is divided into three parameters, where each measure consists of a number of sub-metrices used to calculate the overall score for that specific parameter. The overall ESG score is then calculated by equally weighting the three parameters. Environmental consists of three metrices, social of eight and governance of 37. Environmental factors include, among others, data on carbon reserves and oil used in total production. Social metrics focus among other things on diversity and human rights, whereas governance factors include compensations and management structure. The ESG score is not only a measure of how well the company performs within the different parameters, but also how much they disclose. Therefore, it is not only a score concerned with ethics, but also with the level of transparency. (Bloomberg, 2019)

5.4.1 Dataset

Below tables (Table 12 and Table 13) represent the companies used for the analysis. The initial dataset with S&P 500 companies and their corresponding companies have been narrowed down to 463 companies. This is due to a lack of historical stock prices for 37 of the companies. These companies have either been excluded if the publicly traded period falls below two years or the company has gone through mergers that makes the historical data inconsistent within our time period.

Table 12 - Total Number of Firms Included

Steps	**Amount**	**Total**
Total amount of companies		500
Exclude firms which historical stock data cannot be obtained, or only limited data is available	37	463
Total number of firms		**463**

Thus 463 companies listed in the US and all in the large cap category remains. The data is furthermore divided into sectors, with the financial sector being overrepresented with 99 companies. The least represented sector is materials with just 20 companies.

Table 13 - Overview of Sectors Represented in the Sample Dataset

Industry	**Number of companies**
Communications	21

Consumer Discretionary	69
Consumer Staples	32
Energy	29
Financials	99
Health care	54
Industrials	52
Materials	20
Technology	60
Utilities	27

After materials, communications make up the second least amounts with 21 companies following utilities with 27. Energy has 29 companies represented and consumer stables have 32. With significantly more companies in sectors industrials, health care and technology with 52, 54 and 60 respectively. Consumer discretionary make up the second largest part of dataset with 69 companies.

Table 14 – Number of Stock Exchanges Included in Sample Dataset

Name of stock exchange	**Number of companies**
New York Stock Exchange (NYSE)	363
Nasdaq	99
Bats	1

Companies are primarily listed on New York Stock Exchange with 363 out of 463, as the above distribution shows. Nasdaq includes 99 companies, whereas Bats has one company represented. The stock exchange to which the company is listed will not play a further role in this paper and is simply included for informational purposes.

6 Empirical Analysis

Derived from the main purpose of the thesis, to study the relationship between ambient air pollution in New York City and corresponding investments made on American companies, four main hypotheses were constructed. In the following section these hypotheses will be analysed, and the results will be discussed.

6.1 Hypotheses I

Firstly, this thesis wishes to establish an evidence-based connection between ambient air pollution measured within New York City, represented by $PM_{2.5}$ emissions, and the stock market returns at the New York Stock Exchange. Arising from this is the first hypothesis:

1. ***Ambient air pollution infers a negative impact on stock market return***

6.1.1 The Econometric Model

Constructing a model to investigate the effects of $PM_{2.5}$ on stock market returns on NYSE, the estimation is made with ordinary least squares (OLS), using the following equation:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \beta_3 PM_{2.5,t} + \beta_4 T_t + \beta_5 dDP + \beta_6 AP_t + \beta_7 V_t + \beta_8 WS_t + \beta_9 P_t + \beta_{10} SD_t + \beta_{11} F_t + \beta_{12} H_t + \beta_{13} J_t + \beta_{14} M_t + \varepsilon_t$$

In order to build the econometric model, previous findings in the literature were considered. The dependent variable, r_t, describes the logarithmic return of NYSE in time t. The model includes two lags of the dependent variable (r_{t-1} and r_{t-2}) to control for potential residual autocorrelation, meaning controlling for potential momentum within the market that could affect the results.

$PM_{2.5,t}$ is the independent variable describing the ambient air pollution of particulate matter with a diameter of less than 2.5 micrometres. As mentioned in section 5.2, weather conditions have a proven effect on stock market returns and are thus included into the equation. Temperature (T_t), dew point (DP_t), air pressure (AP_t), visibility (V_t), wind speed (WS_t), precipitation (P_t) and snow depth (SD_t) are all numerical variables. Fog (F_t) and haze (H_t) are both dummy weather variables. These are included to control for their effects.

January (J_t) and Monday (M_t) are both dummy variables included to control for their positive and negative effects on stock market returns respectively. These effects have been discussed in section 5.3. Lastly, εt indicates the error term and β_0–β_{14} are the OLS coefficients.

6.1.2 Empirical Results

Table 15 below contains the results from the regression, including the estimate and p-value. The statistical significance test provides a rudimentary way of depicting the effect variables have on the dependent variable.

Table 15 – Empirical Results for Hypothesis I Regression

Variable	Estimate (%)	P-value
1-day lagged log return, r_{t-1}	0.4369	0.8774
2-day lagged log return, r_{t-2}	-2.6840	0.3440
$PM_{2.5}$, $PM_{2.5,t-2}$	0.0135*	0.0543
Temperature, T_t	0.0038	0.4611
Dew Point, DP_t	-0.0038	0.4214
Air Pressure, AP_t	0.0016	0.6702
Visibility, V_t	0.0203	0.3692
Wind Speed, WS_t	0.0049	0.5803
Precipitation, P_t	-0.0047	0.9537
Snow Depth, SD_t	-0.0098	0.5688
Fog, F_t	0.1682**	0.0154
Haze, H_t	-0.0264	0.7123
January, J_t	0.0925	0.3179
Monday, M_t	0.0756	0.1942
Constant	-2.0850	0.5840

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

The coefficient on $PM_{2.5}$ is statistically significant at the ten percent level and, contradicting Hypothesis I, positive, showing how an increase of one unit of $PM_{2.5}$ will result in an increase of daily returns of 0.0135 percent. The only other significant variable arising from the model is fog, which also seems to have a positive effect on daily returns. As fog is a dummy variable, a statistically significant estimate shows that if the weather is indeed foggy that day, daily returns of the same day will increase with 0.1682 percent.

$PM_{2.5}$ can remain within the body for several days leading to a delayed effect. Coherent with this, Bullinger (1989) described through her studies, that air pollution can affect stock market returns up to four days after exposure to air pollution. It is thus essential to examine lagged effects and thus control for any cumulative effects of air pollution. Results here from can be seen in Table 23 in the appendix.

It becomes evident from testing lagged versions of the $PM_{2.5}$ variable, that the variable lagged two periods are consistently significant and negative throughout. Aside from the original model constructed, the same day $PM_{2.5}$ is never significant. From this it can be concluded that ambient air pollution does have a negative, but delayed, impact on stock market returns, confirming the initial hypothesis.

Identically to the tests conducted on the independent air pollution variable, $PM_{2.5}$, tests on whether the weather variables have delayed effects has been conducted. The results hereof can be seen in Table 24 in the appendix. Tests shows that the variables for temperature, dew point, visibility, wind speed and precipitation all remain statistically insignificant throughout all periods, all consistent with the findings of the original regression. Air pressure is statistically significant at a ten percent level when lagged three periods included into a regression containing all four lags. Looking at this, it is concluded that nothing significant can be said about the result as it is not consistent throughout. An interesting finding becomes evident when testing the variable for snow depth. Here, like for $PM_{2.5}$, a delayed negative effect is discovered. In three out of five regressions a single period lag shows statistical significance at a five percent or ten percent level.

Arising from the above testing, it can be concluded that snow depth has a delayed negative impact on stock market returns, whereas all other weather variables seem statistically insignificant.

6.1.3 Sensitivity Analysis

As discussed in methodology, the regressions build upon the assumption that the main independent variable, $PM_{2.5t}$, is uncorrelated with the error term, εt. It has additionally been discussed how weather variables also affect stock market return. This is the reason why they have been included into the model. Hence, it is therefore important to ensure air pollution and weather variables do not correlate too closely, and thus a sensitivity analysis has been conducted.

In order to conduct the robustness-test, several deconstructed versions of the model have been built, and the results are displayed in Table 25 in the appendix. Firstly, a model only containing the dependent and the main independent variable was made. This model resulted in an estimate of 0.0103 compared to 0.0135 in the original model, still significant at a ten percent level. This difference is not great, and the variable is still significant. The second model only excludes all weather variables, numerical and dummy variables, now only containing $PM_{2.5}$ and the dummy for January and Monday. Results show the estimate for $PM_{2.5}$ is significant at a ten percent level and at a value of 0.0104, almost identical to the one only containing $PM_{2.5}$. If the estimate of $PM_{2.5}$ was to differ greatly from the one displayed above, a high correlation between weather variables and $PM_{2.5}$ is present. Since the exclusion of the weather variables did not make notable changes, weather variables do not correlate with $PM_{2.5}$. Lastly, a model only including $PM_{2.5}$ and the only significant weather variable, fog, resulted in an estimate of 0.0112 significant at a ten percent level. In line with the above tests, the change is not great.

6.1.4 Conclusion

Looking into the testing of how ambient air pollution affects stock market returns, a hypothesis arguing a negative correlation was used as foundation. Based on this hypothesis, an OLS regression was constructed using daily log returns from the NYSE Composite Index, hourly measurements of $PM_{2.5}$ as well as controlling weather and seasonality variables. When conducting the regression, it is found that the air pollution indeed is significant in explaining the movements in stock market returns. Yet, the sign of the estimator is not as expected, as the estimate reads an increase in one unit of $PM_{2.5}$ infers an increase in daily log return of 0.0135 percent.

Instead of immediately rejecting the initial hypothesis, lagged versions of the $PM_{2.5}$ variable were included into the model to test for delayed effects. Here it was found that $PM_{2.5,\, t-2}$ was consistently significant and negative. On the basis of this knowledge it is possible to confirm Hypothesis I, stating air pollution's negative impact on stock market returns, concluding that $PM_{2.5}$ has a delayed negative effect on stock market returns.

6.2 Hypothesis II

Discovering that indeed there is a negative effect on stock market returns arising from high levels of ambient air pollution, confirming Hypothesis I, allows the authors to continue and further explore. Succeeding this, this thesis' second objective is to discover whether there is a significant difference in returns between companies holding a high ESG score and those with a low ESG score. The second hypothesis is thus:

> ***2. During periods with high levels of ambient air pollution, stocks with high ESG scores outperform lower scoring stocks***

6.2.1 The Econometric Models

When investigating the above stated hypothesis, two econometric models have been built as to compare high and low scoring companies' performance. Both models are, like Hypothesis I, OLS regressions. Firstly, the model describing the performance of the high scoring companies:

$$r_t = \beta_0 + \beta_1 ESG_t^H + \beta_2 v_t^H + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Secondly, the model describing the performance of the low scoring companies:

$$r_t = \beta_0 + \beta_1 ESG_t^L + \beta_2 v_t^L + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

The dependent variable, r_t, defines the average return across the included companies as a proxy for the overall return on the market. ESG scores for high and low scoring companies have been included as ESG_t^H and ESG_t^L respectively. Included into the model are v_t^H and v_t^L, depicting the trade volume. The included trade volume is utilised as a measure of activity, measuring if there is more or less activity in either of the portfolios. Continuing the exploration of the effects of ambient air pollution on stock market returns, two period lagged daily measures of $PM_{2.5,t-2}$ has been included into both models. Lastly, $\beta_0 - \beta_3$ are the OLS coefficients and ε_t determine the standard error term of the models.

6.2.2 Empirical Results

Initially, below in Table 16, the empirical results of the first model, exploring the performance of high scoring companies are presented. The table reports the OLS coefficients as well as the p-values for the paired significance tests.

Table 16 – Empirical Results for High Scoring Companies' Performance

Variable	Estimate (%)	P-value
High ESG score, ESG_t^H	0.0027**	0.0442
High trade activity, v_t^H	0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0055*	0.0701
Constant	0.1533	0.1304

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Firstly, evaluating the effects of high ESG scores ability to explain the average stock market return across all included companies is the ESG_t^H variable. The variable ESG_t^H is statistically significant at a five percent level. Reading the OLS coefficient shows how a one-point increase in the ESG score will infer a 0.0027 percent increase in stock market returns. Furthermore, looking at the trade activity variable, it is strictly speaking statistically significant. Daily trade activity is statistically significant at a one percent level, but the OLS coefficient is so small it has been registered at zero with a corresponding p-value of zero. Continuing slightly on the findings of Hypothesis I, results show how ambient air pollution remains statistically significant at a ten percent level under further model construction. The two-day lagged air pollution variable, relative to the non-lagged variable, was included due to its proven statistical significance in the previous section. The effects on the average stock market returns are negative, again, showing how an increase in air pollution will lead to a decrease in daily stock market returns. A one unit increase in $PM_{2.5}$ infers a 0.0055 percent decrease in stock market returns two days later.

Similar to the analysis of the high scoring companies above, Table 17 displays the summary statistics of the low scoring companies.

Table 17 – Empirical Results for Low Scoring Companies' Performance

Variable	Estimate (%)	P-value
Low ESG score, ESG_t^L	-0.0025	0.3066
Low trade activity, v_t^L	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0064**	0.0369
Constant	0.3798***	0.0021

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Unlike the high scoring companies, the low ESG scores do not seem to be statistically significant in terms of explaining the movements of the average daily stock market returns. Another interesting result is the sign of the ESG variable, which indicates that a one-point increase in ESG scoring will infer a decrease of 0.0025 percent in stock market returns. Identical with the high scoring companies, trade activity is statistically significant at a one percent level with an OLS coefficient registering at zero. The corresponding p-value is also registered at zero. Continuing the inclusion of the two-day lagged ambient air pollution variable, $PM_{2.5}$, shows statistical significance at a five percent level with a negative sign. This means that for low scoring companies a one unit increase in $PM_{2.5}$ leads to a decrease of stock market returns of 0.0064 percent two days later.

In assessing whether high scoring companies indeed outperform the lower scoring companies it is necessary to directly compare the two OLS regressions through the ESG estimates. Table 16 and Table 17 depict, how having a high ESG score results in an increase in stock market returns. Likewise, as having a low ESG score leads to a decrease in stock market returns. Yet, this effect is only shown to be statistically significant for the high scoring companies. It is possible to determine the degree of outperformance by calculating the difference between coefficients.

$$Diff = ESG_t^H - ESG_t^L$$

⇔

$$= 0.0027 - (-0.0025) = 0.0052$$

Concluding from this, the average stock market returns of the high scoring companies is 0.0052 percent higher compared to that of the lower scoring companies. Thus, from this initial analysis it is seen how companies with a high ESG score outperforms companies with a low ESG score in terms of stock market returns.

6.2.3 Sensitivity Analysis

One issue arising from the above analysis, is the statistical insignificance of the ESG_t^L coefficient. Thus, the comparison and higher scoring companies' outperformance of lower scoring companies cannot be said to be statistically significant. In order to test whether the above-mentioned conclusion is indeed significant, a model consisting of the differences between ESG variables have been made.

$$r_t = \beta_0 + \beta_1 ESG_t^{H-L}$$

With an offset in the model outlined, only including the dependent average return variable and the ESG variable for the high scoring companies minus the one of the low scoring companies, the following results have been made. The results are depicted in Table 18 below.

Table 18 – Empirical Results on High Minus Low Scoring Companies' Performance

Variable	Estimate (%)	P-value
HML ESG score, ESG_t^{H-L}	0.0054*	0.071
Constant	-0.1156	0.156

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Through the sensitivity analysis, an estimate of 0.0054 percent for the hedged ESG score was found. This estimate is very close to the one calculated by subtracting the low ESG estimate from the high ESG estimate (0.0052). Further investigation of whether this continues to hold true when adding trade activity and air pollution to the regression, is done below.

A sensitivity analysis of the high-minus-low ESG coefficient has been conducted in order to examine, whether the difference remains statistically significant when alone, including trade volume and lastly including $PM_{2.5}$. The results hereof can be seen in Table 26 in the appendix. Derived from the sensitivity analysis is an ESG_t^{H-L} coefficient which is consistently statistically significant when adding more variables to the model. As discovered above, including only the ESG variable results in a coefficient of 0.0054, statistically significant at a ten percent level. When adding the variable of the difference in trade activity, v_t^{H-L}, the ESG coefficient is increased to 0.0152 and significant at a one percent significance level. Now, instead of affecting the stock positively with only 0.0054 percent, the effect has increased to 0.0152 percent. Including trade activity in the model has thus almost tripled the difference in performance between high and low scoring companies. Constructing the final model, including the measure of $PM_{2.5}$, the coefficient of ESG is 0.0150 with a statistical significance level of one percent. Adding ambient air pollution to the model maintains a high difference between performance of the two company portfolios.

From Hypothesis I it became evident that the effects of the ambient air pollution were negative and delayed as well as fog being statistically significant as well. Fog is not initially included into the high and low ESG regressions. This section of the sensitivity analysis will explore whether fog plays a significant role in explaining stock market returns when connected with either high or low scoring companies. The results of the sensitivity analysis can be seen in Table 27 in the appendix.

Lastly, fog was inserted into the full models. As shown in Panel A in Table 27, the fog variable shows no sign of statistical significance. The fog coefficient shows a negative sign, which is inconsistent with the findings in Hypothesis I, showing a positive sign. Furthermore, the analysis shows how the inclusion of fog does not change the statistical significance of the high ESG score, nor change the sign or the size of the coefficient considerably. Panel B in the same table depicts the results from including fog into the low ESG scoring regression. Once again, the variable showed no statistical significance, yet the sign of the coefficient was negative. Again, the value and sign of the ESG coefficient remained with the same sign and almost entirely unchanged. With a base in this analysis, it can be concluded that fog is not significant in either of the regressions of Hypothesis II.

6.2.4 Conclusion

Testing whether companies with a high ESG score outperforms companies with a low ESG score under the presence of ambient air pollution leads to the construction of two separate models. These models were run individually, showing how a high ESG score positively affects your stock market return and vice versa for low ESG scores. Estimates of 0.0027 and -0.0025 were derived for the two portfolios respectively. Yet, only results for the high ESG portfolio proved to be statistically significant. Based on these results it was possible to establish an initial analysis stating that high ESG scoring companies indeed outperformed low ESG scoring companies with 0.0052 percent. One problem occurred during this, which was the lack of statistical significance to the result.

Instead of rejecting the null hypothesis, a sensitivity analysis was conducted modelling the difference in performance between the two groups of companies. This elaborated analysis revealed how a high-minus-low coefficient showed a statistical significance with a value of 0.0054 percent, thus very close to the one discovered during the initial analysis. The high-minus-low coefficient became increasingly statistically significant and increased in value as the final model was constructed including both trade activity and air pollution. Conclusively, it is thus possible to say that companies with a high ESG score outperforms companies holding a low ESG score in the presence of ambient air pollution.

6.3 Hypothesis III

Following Hypothesis II's conclusion that high ESG scoring companies do outperform low ESG scoring companies, measured in terms of stock market performance comes Hypothesis III. This hypothesis questions whether differences among the three components, E, S and G, are present. If this is the case, it would suggest that investors weigh the importance of the three components differently. Based on this the individual environment, social and governance scores will be studied respectively through the following:

> ***3. The three components of the ESG score (environment, social and governance) weigh differently in importance during decision-making of pollution affected investors***

6.3.1 The Econometric Models

Maintaining the same reasoning as presented in Hypothesis II, multiple OLS regressions will be constructed in the investigation of Hypothesis III. The models have been built as to depict the impact the three ESG measures each has on the overall average stock market return. The first model investigates the impact of the environmental component, E:

$$r_t = \beta_0 + \beta_1 E_t + \beta_2 v_t^E + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

The second model investigates the impacts of the social component, S:

$$r_t = \beta_0 + \beta_1 S_t + \beta_2 v_t^S + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Finally, the third model investigates the impacts of the governance component, G:

$$r_t = \beta_0 + \beta_1 G_t + \beta_2 v_t^G + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

The dependent variable, r_t, is the average daily return on the included companies. Each of the regressions consists of one of the three ESG components; environmental (E_t), social (S_t) or governance (G_t). The variables represent the average E, S and G score across the included companies. Like the regressions in Hypothesis II, v_t in the trade activity. Here, the trade activity is measured as the average trade activity across all companies. Lastly, $PM_{2.5,t-2}$ is the two days lagged ambient air pollution variable. The betas ($\beta_0 - \beta_3$) are OLS coefficients and ε_t is the standard error term.

6.3.2 Empirical results

The results of the exploration of the three ESG components will be presented one component at a time followed by an overall summary. Firstly, the results from the analysis of the environmental component (E) is presented below in Table 19. The table shows both the OLS coefficient estimates and corresponding p-values.

Table 19 – Empirical Results for the Environment (E) Score

Variable	Estimate (%)	P-value
E score, E_t	-0.0040	0.3232
Trade activity, v_t^E	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0002	0.9463
Constant	0.5413***	0.0004

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

As shown in the table above all the variables except the constant are negative, which is unexpected. A negative sign for the E score estimate means that an increase in the E score leads to a decline in the stock market return of 0.0040 percent. What is also striking is the fact that this estimate is not statistically significant, like the full high and hedged ESG scores of Hypothesis II.

When looking at the impact of trade activity, the same results as found for both regressions in testing of Hypothesis II are found. The impact of trade activity is statistically significant but insignificant in size. What is interesting is the sign of the estimate. According to the negative sign, an increase in trade activity leads to a decrease in stock market returns. Continuing, by looking at the coefficient for a two-day lagged ambient air pollution, $PM_{2.5}$. This is not significant in this setting, which indicates that ambient air pollution does not have the same lagged effect on environmental stocks the same way it has on ordinary as well as ESG scoring stocks. The sign of the coefficient remains negative, indicating a non-significant, yet negative impact.

Elaborating this, the impact of social (S) scores revealed the following results displayed in Table 20 below.

Table 20 – Empirical Results for the Social (S) Score

Variable	**Estimate (%)**	**P-value**
S score, S_t	-0.0000	0.9740
Trade activity, v_t^S	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0004	0.9100
Constant	0.3938***	0.0057

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Looking at the results from testing the social score separately, they are very similar to the ones obtained in the above test of the environmental score. The S score estimate is negative and statistically insignificant. Furthermore, the estimate of the S variable is insignificant in size. All this combined shows how the S score all together seems to have no impact in determining fluctuations in stock market returns. Continuing to the estimate of trade activity, this estimate is statistically significant but insignificant in size as it is too small. This is in accordance with the results of trade activity in Hypothesis II and the above test of the E score. Yet, the sign is interesting as this shows that an increase in trade activity leads to a decrease in stock market returns. Lastly, the lagged ambient air pollution estimate is not statistically significant in this regression but remains negative. This suggests that $PM_{2.5}$ does not have the same impact on stock market returns combined with the social score as it had when including the full ESG score. Yet, the effects are negative as expected.

To sum up the tests of Hypothesis III, the results of the third regression testing the impact of the governance (G) score are presented in the table below (Table 21).

Table 21 – Empirical Results for the Governance (G) Score

Variable	Estimate (%)	P-value
G score, G_t	-0.0045	0.5530
Trade activity, v_t^G	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0002	0.9580
Constant	0.7377	0.1900

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

The results derived from the third regression show similarities to the ones found in the previous two regressions. All estimates are negative, with the exception of the constant. Again, the estimate of the G score is negative and statistically insignificant, meaning that an increase in score will lead to a decrease in stock market returns. The trade activity estimate is also negative and like for E and S statistically significant but insignificant in size. As mentioned earlier, this is coherent with results found when testing E, S and ESG scores. Finally, the estimate for $PM_{2.5}$ in continuously negative and statistically insignificant.

6.3.3 Sensitivity Analysis

From the results above it becomes evident that neither E, S nor G scores are statistically significant in themselves when explaining movements in stock market returns. In this section two sensitivity analyses will be conducted. Firstly, an analysis on whether the lack of statistical significance is caused by the inclusion of other variables. This is why, smaller interim models will be constructed. Secondly, an analysis will explore whether statistical insignificance changes, when conducting the same analysis but separating high and low E, S and G scores.

The construction of interim models leads to testing with the E, S or G score being the sole independent variable, including trade activity and lastly adding ambient air pollution to the regression. In Table 28 in the appendix the results show that for none of the interim models, either of the scores were statistically significant. Looking further into the results, it becomes apparent that for all the initial models, where the E, S or G score is the sole independent variable, the estimates are positive. This shows that an increase in the E, S or G score will lead to an increase in stock market returns. What is even more interesting and consistent with the results from the original analysis is, when including trade activity and later on $PM_{2.5}$, all estimates are negative. Including more variables to the regression thus alters the sign of the estimates, meaning that an increase in either the E, S or G score will infer a decrease in stock market returns. Despite neither of the estimates being statistically significant, the results found in this sensitivity analysis remain counterintuitive.

Continuing the sensitivity analysis with an exploration of the potential difference in outcome, which might be present when including high and low scores separately, hereby conducting a sensitivity analysis similar to Hypothesis II. Here, the same interim models have been constructed and run, testing the impacts of high, low and hedged (high-minus-low) variables. The results of this analysis can be found in Table 29 in the appendix, where panel A, B and C show results for the E, S and G scores respectively. Looking into the result of the initial model, with only one (E, S or G) independent variable, none of the estimates are statistically significant. All estimates with the exception of the high G score and the high-minus-low G score are positive, suggesting a positive impact on stock market returns when increased in score. The second model, including trade activity, mainly shows negative estimates. The high E score is positive but not statistically significant, whereas both the low E and the high-minus-low E score are statistically significant at a one percent level. Low E scoring companies have a negative estimate of -0.0253, but the estimate for the high-minus-low is positive at 0.0115. Furthermore, looking at the results in panel B, only the high-minus-low estimate for the S component shows statistically significant. This at a one percent level with a value of -0.0068. Two out of three estimates, being the low and the high-minus-low, are negative which is consistent with above results. Panel C displaying the results of the governance component shows no statistical significance in any of the estimates and all are negative.

Finally, a full model including the E, S or G score, trade activity and $PM_{2.5}$ have been constructed for high, low and high-minus-low variables. For the environmental score, the results are similar to the ones excluding the ambient air pollution. Only the low E score and the high-minus-low score are statistically significant, and this at a one percent level. The estimates for the low score and the hedged score are -0.0250 and 0.0123 respectively. Thus, the estimates do not only remain statistically significant and with the same sign, they also remain with an almost identical value. This means that the ambient air pollution does not influence the impact on stock market returns arising from the E score. Like the environmental measure, the social component also shows similar results with and without the inclusion of the air pollution. Again, only the hedged variable shows statistical significance at a one percent level, with a value of -0.0069. Both the high and the low G scores have estimates almost identical to the ones in the model without $PM_{2.5}$. The governance component has until this point had no statistically significant estimates in neither the initial model nor with the inclusion of trade activity. When including $PM_{2.5}$, the high G scoring estimate show statistical significance at a five percent level with an estimate of -0.0428. The estimates of the high, the low as well as the high-minus-low G scores remain close to identical in both latter models.

6.3.4 Conclusion

Hypothesis III explored the potential differences in significance and size of estimates within the three separate components of the ESG score; environmental, social and governance. The conclusion from this analysis is that there seems to be no difference between the three components. All three, when included into the full model, showed no statistical significance and a negative sign. These results suggest that an increase in either of the three components infers a decrease in stock market returns, which is counterintuitive when considering the results of Hypothesis II. Furthermore, in neither of the three models estimates for $PM_{2.5}$ show any statistical significance, suggesting they have no predictive power in determining the conjunctions of the stock market returns. All three remain negative signifying a negative impact, which is coherent with previous results.

Conducting a sensitivity analysis revealed that no matter the regression composition, all three scores were statistically insignificant. What was interesting was the change in sign, from negative to positive, when adding other variables to the regression. Thus, implying the extra variables causes a shift from a positive to a negative effect on stock market returns. Further exploring whether there might be a difference when looking at high versus low scores, the sensitivity analysis resulted in some statistical significance. The full models, including both the E, S or G score, trade activity and air pollution had the most statistically significant estimates. Here, both the low and the hedged model estimates were statistically significant at a one percent level for the environmental score. The social score only showed statistical significance for the hedged score, whereas the governance score was significant in the high scores. All significant results were negative, signifying increases in scores will lead to decreases in stock market returns. These results are also inconsistent with the results of Hypothesis II, concluding how an increase in the full ESG score leads to an increase in stock market returns.

6.4 Hypothesis IV

Hypothesis IV will conduct a sector analysis, assuming investors might be sector biased. The same way Hypothesis III was tested for bias in ESG components, this analysis will separately test the sectors included in the dataset. Based on the assumption of investors' sector bias, the following hypothesis has been developed.

4. ***Within certain sectors ESG scores weight more heavily on investment decisions relative to other sectors***

6.4.1 The Econometric Models

As mentioned above in the introduction to the final hypothesis of this thesis, this analysis will investigate the sectors included separately. In the ESG data obtained from Bloomberg, all the companies included were segmented into a total of ten sectors: Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Materials, Technology and Utilities. The ten regressions being analysed during this section of the thesis is presented below.

Communication

$$r_t = \beta_0 + \beta_1 ESG_t^{com} + \beta_2 v_t^{com} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Consumer discretionary

$$r_t = \beta_0 + \beta_1 ESG_t^{CD} + \beta_2 v_t^{CD} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Consumer staples

$$r_t = \beta_0 + \beta_1 ESG_t^{CS} + \beta_2 v_t^{CS} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Energy

$$r_t = \beta_0 + \beta_1 ESG_t^{nrg} + \beta_2 v_t^{nrg} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Financial

$$r_t = \beta_0 + \beta_1 ESG_t^{fin} + \beta_2 v_t^{fin} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Health care

$$r_t = \beta_0 + \beta_1 ESG_t^{HC} + \beta_2 v_t^{HC} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Industrials

$$r_t = \beta_0 + \beta_1 ESG_t^{ind} + \beta_2 v_t^{ind} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Materials

$$r_t = \beta_0 + \beta_1 ESG_t^{mat} + \beta_2 v_t^{mat} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Technology

$$r_t = \beta_0 + \beta_1 ESG_t^{tech} + \beta_2 v_t^{tech} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

Utilities

$$r_t = \beta_0 + \beta_1 ESG_t^{uti} + \beta_2 v_t^{uti} + \beta_3 PM_{2.5,t-2} + \varepsilon_t$$

In all regressions the dependent variable, r_t, is the average daily stock market return of the included companies. ESG represents the ESG score for the analysed sector across all companies within that sector. Also included into the model is the trade activity within the sector, which is incorporated through v_t. All regressions also include the two-day lagged ambient air pollution variable, $PM_{2.5,t-2}$. Lastly, the betas ($\beta_0 - \beta_4$) are the OLS coefficients where ε_t represents the regression's error term.

6.4.2 Empirical Results

This section of the thesis will explore and explain the results derived from the ten analyses conducted. These results will be presented in one larger table in order to provide a better overview. The table below (Table 22) displays the results from analysing all ten sectors included. This shows the results in panel A through J representing the sectors from communications through utilities as listed above.

Table 22 – Empirical Results for the Ten Sector Analysis

Variable	Estimate (%)	P-value
Panel A		
ESG score, ESG_t^{com}	0.0033	0.2718
Trade activity, v_t^{com}	0.0000**	0.0237
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	0.0008	0.8364
Constant	-0.1310	0.3118
Panel B		
ESG score, ESG_t^{CD}	0.0003	0.9144
Trade activity, v_t^{CD}	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0016	0.6610
Constant	0.3534*	0.0405
Panel C		

ESG score, ESG_t^{CS}	0.0010	0.6663
Trade activity, v_t^{CS}	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0007	0.8573
Constant	0.2959*	0.0636
Panel D		
ESG score, ESG_t^{nrg}	0.0024	0.1593
Trade activity, v_t^{nrg}	-0.0000***	0.0008
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0007	0.8587
Constant	0.0965	0.3500
Panel E		
ESG score, ESG_t^{fin}	0.0028	0.1190
Trade activity, v_t^{fin}	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0011	0.7770
Constant	0.1603	0.1080
Panel F		
ESG score, ESG_t^{HC}	0.0025	0.2146
Trade activity, v_t^{HC}	-0.0000**	0.0163
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0009	0.8000
Constant	0.0700	0.5587
Panel G		
ESG score, ESG_t^{ind}	0.0001	0.9741
Trade activity, v_t^{ind}	-0.0000***	0.0000

2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0011	0.7780
Constant	0.2604**	0.0351
Panel H		
ESG score, ESG_t^{mat}	0.0020	0.1175
Trade activity, v_t^{mat}	-0.0000***	0.0082
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0010	0.7973
Constant	0.0629	0.4698
Panel I		
ESG score, ESG_t^{tech}	0.0006	0.8392
Trade activity, v_t^{tech}	-0.0000***	0.0012
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0016	0.6651
Constant	0.2249	0.1903
Panel J		
ESG score, ESG_t^{uti}	0.0001	0.9660
Trade activity, v_t^{uti}	-0.0000***	0.0000
2-day lagged $PM_{2.5}$, $PM_{2.5,t-2}$	-0.0008	0.8360
Constant	0.3121**	0.0100

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

When exploring the results presented above, it becomes evident that none of the estimates for the sector ESG scores are statistically significant. Furthermore, all of them are positive, ranging from 0.0001 to 0.0033, meaning a one-point increase in ESG score will thus infer an increase of 0.0001 percent to 0.0033 percent increase in stock market returns. The lowest impacts of ESG score increase are seen in the industrial and utilities sectors, which both have an estimate of only 0.0001 percent. Following closely in the low estimates is the consumer discretionary sector at 0.0003 percent and the technology sector at 0.0006 percent. On the other hand, the highest impacts are realised in the communications sector (0.0033 percent), the financial sector (0.0028 percent) and the health care sector (0.0025 percent). The positive effect on stock market returns as a result of the increase in ESG scores are coherent with the results discovered for the high ESG scoring companies as well as the individual E, S and G components.

Continuing by investigating the coefficients of trade activity, all sectors show statistical significance at a five percent or one percent level. Additionally, all the estimates are negative except for the communications industry. This means an increase in sector trade activity will cause a decrease in stock market returns. What should be noticed though, is the fact that all estimates are measured at 0.0000 percent, positive and negative, leading to the estimate becoming uninfluential due to size. This suggests that trade activity has no explanatory power when investigating stock market return fluctuations.

Lastly, the two-day lagged effects of the ambient air pollutant $PM_{2.5}$ were examined when incorporated into sector specific settings. Identical to the estimates of the ESG scores, none of the $PM_{2.5}$ estimates are statistically significant and like the trade activity estimates all the $PM_{2.5}$ estimates are negative except for the communications sector. The negative sign before the pollution estimate induces a decrease in returns caused by an increase in pollution. The size of the estimate ranges from -0.0016 to 0.0008, submitting an impact from -0.0016 percent to 0.0008 percent. The communications industry returns seem to be positively influenced by an increase in air pollution such that a one-unit increase in $PM_{2.5}$ leads to an increase in stock market returns of 0.0008 percent. The two industries mostly negatively influenced by an increase in $PM_{2.5}$ are the consumer discretionary sector and the technology sector both with estimates of -0.0016 percent. Both the financial sector and the industrials sector have estimates of -0.0011 percent, making these the sectors second most affected. Besides the communications industry, experiencing a positive impact, the least negatively impacted industries are the consumer staples industry (-0.0007 percent) and the energy industry (-0.0007 percent).

6.4.3 Sensitivity Analysis

The above empirical results state that none of the industries have statistically significant ESG scores, which is why a two-part sensitivity analysis will be conducted in this section. Through a robustness-test the first part will decide whether autocorrelation influences the significance of the ESG scores. Such an analysis is conducted through the construction of deconstructed interim models ranging from only including the industry ESG score to the full model as depicted above. Secondly, an analysis of high versus low scoring companies within each industry is made to determine potential differences.

Table 30 in the appendix displays the results from the first analysis, presenting ESG score estimates for all sectors in the three deconstructed models. Initiating by looking at the results of the basic model only including the dependent variable, the constant, the error term and the ESG score as independent variables. In all ten sectors, the ESG estimate is not statistically significant and positive with values ranging from 0.0018 to 0.0028. With the lowest effects of 0.0018 percent and 0.0019 percent is the utilities sector and the materials sector respectively. This is opposed to the energy and industrial sector with estimates of 0.0027 percent and the consumer staples sector with 0.0028 percent.

Adding sector trade activity to the model does not alter the lacking statistical significance of all estimates nor the positive sign. Yet, the volatility in results increased to ranging from 0.0001 to 0.0034. Again, the utilities sector shows the lowest impact with a one-point increase in ESG score only leading to a 0.0001 percent increase in stock market returns. The industrial sector (0.0001 percent) also shows a very small influence from ESG scores along with the consumer discretionary sector (0.0002 percent). When adding trade activity to the regression, especially the communications industry is influenced by changes in ESG scores. With an estimate of 0.0034 percent, it is notably larger than the second largest, being the financial sector, with 0.0027 percent.

Finally, adding the effects of the ambient air pollutant, $PM_{2.5}$, to the regression creating the full model does not influence the statistical insignificance of the ESG coefficients. The range of results is almost identical to the second model, with results now ranging from 0.0001 to 0.0033. In the very low end with an estimate of 0.0001 percent is the industrial and the utilities sectors and in the high end, the communication sector with 0.0033 percent. Moreover, the consumer discretionary sector, the financial sector as well as the health care sector, all three experienced an increase in estimate of 0.0001 percentage point. The communications sector and the consumer staples sector both experienced a drop of 0.0001 percentage point, whereas the remaining four sectors did not experience any changes.

From the above sensitivity analysis, it becomes apparent that the ESG scores as an average across each sector is not statistically significant in explaining stock market return fluctuations. Aligned with the sensitivity analysis of Hypothesis II and III, a test of whether there are differences in significance between high and low ESG scores has been made. This analysis is conducted such that each sector's ESG score is inspected in regard to respectively high scores, low scores and high-minus-low scores – hedged scores. The results of this analysis can be seen in Table 31 in the appendix.

The results of the baseline model, including only the ESG score as an independent variable, shows that for none of the ten sectors neither the high nor the low score is statistically significant. High score estimates range from 0.0016 to 0.0050, whereas the low score estimates range from 0.0016 to 0.0034. Looking at the hedged variables, estimates for the consumer discretionary sector (0.0166), the industrial sector (0.0078), the technology sector (0.0080) and the utilities sector (0.0133) show statistical significance at a one or five percent level. The lowest hedged estimate, and the only negative estimate in the baseline model tests, was -0.0120 percent for the communications sector.

When adding trade activity to the regression, more statistically significant results occur. Initiating with an investigation of the high scoring estimates, results show that estimates for the communications sector, the consumer discretionary, the consumer staples sector, the energy sector, the technology sector and the utilities sector show no statistical significance. The financial sector as well as the health care sector have estimates that are significant at a ten percent level with values of 0.0024 percent and 0.0029 percent respectively. Looking at the material sector, the coefficient has a value of 0.0029 and is significant at five percent, where the industrial sector has an estimate of 0.0050, which is significant at a one percent level. All high ESG scoring coefficients range in value from 0.0003 to 0.0050. Only two of the sectors show statistically significant estimates for the low ESG scores, which is the consumer discretionary sector (-0.0091) and the industrial sector (-0.0077). Both show negative signs and are significant at a five percent level. Overall, the range of estimates is from -0.091 (consumer discretionary) to 0.0027 (health care). Six out of ten of the hedged estimates are statistically significant, ranging in significance between one and ten percent. The significant estimates pairs with the consumer discretionary sector (0.0290), the financial sector (0.0060), the health care sector (0.0095), the material sector (0.0064), the technology sector (0.0141) and the utilities sector (0.0133). All coefficients are positive except for the communications sector, which has a value of -0.0067.

Ultimately, the full model results are discussed. Estimates for the high ESG scoring companies range from 0.000 to 0.0052, with the lowest scoring sector being the consumer staples sector and the highest scoring the industrial sector. Six out of ten sectors show statistically significant coefficients with significance levels varying from one to ten percent. Lower ESG scoring estimates are negative in four out of the ten sectors, and statistically significant in only two out of the ten sectors. Both sectors with significant coefficients, the consumer discretionary sector and the industrial sector, have negative estimates with values of -0.0090 and -0.0075 respectively. Examining the results from the hedged variables show estimates ranging from -0.0073 (communication sector) to 0.0310 (consumer discretionary sector). The communications sector is the only sector with a negative estimate and this estimate shows no statistical significance. Six of the ten sectors have statistically significant, positive estimates with values from 0.0060 (material sector) to 0.0310 (consumer discretionary sector). The statistical significance scope of the coefficients is one to ten percent.

6.4.4 Conclusion

Hypothesis IV investigated whether differences in the influence from increases in ESG scores were present across ten sectors. From the original analysis evidence proved that there was no statistical proof of such. None of the ten ESG score estimates showed any statistical significance. Furthermore, these estimates all had identical, positive signs suggesting a positive correlation. This concludes a one-point increase in ESG score will in all ten sectors infer an increase in stock market returns ranging from a 0.001 percent to a 0.0033 percent increase.

Testing the robustness of the results, a two-part sensitivity analysis was conducted testing potential inference from autocorrelation with other variables as well as potential differences across high versus low scoring sectors. The initial robustness test did not revise the results of the initial analysis as neither of the deconstructed models showed any statistically significant ESG estimates. While further studying potential distinctions among high, low and hedged scores some statistical significances were discovered. Especially among the hedged estimates statistical significance was present, which suggest that it is the difference between high and low scores that impact stock market returns rather than the score itself. Consistent with former conclusions, the majority of the significant estimates were positive suggesting an increase in ESG score does have a positive effect on stock market returns.

6.5 Conclusion of Analysis

When studying the impact of ambient air pollution in New York City on stock market returns, lead to an array of interesting discoveries. Furthermore, not only the analysis of whether pollution impacts stock market returns, but also what influence pollution has on sustainable investment, derived striking conclusions.

Initiating with the conclusions obtained from Hypothesis I, stating that ambient air pollution infers a negative effect on stock market returns. This was tested through the construction of an OLS regression containing the pollutant $PM_{2.5}$, various weather variables and seasonality control variables. The main result was the statistically significant, negative relationship between ambient air pollution and stock market returns. A negative relationship would suggest that an increase in pollution would lead to a decrease in stock market returns. The effect observed was lagged with two periods, meaning delayed two days. Thus, two days after investor exposure, the market experienced a decrease in returns. As mentioned, the model also included weather variables, where only fog proved statistically significant. The meaning of this significance will be discussed further in the discussion section.

Once the delayed, negative relationship between air pollution and stock market return, the second hypothesis included a measure of company sustainability – the ESG score. Here the hypothesis stated that more sustainable companies outperform less sustainable companies, proxied by their ESG score, given the presence of ambient air pollution. This laid the foundation for the creation of two portfolios; a portfolio with High ESG scores and a portfolio of low ESG scores, divided by the median. The high ESG score proved to be statistically significant with a positive estimate, implying a positive relationship between a high ESG score and stock market returns. On the other hand, the low ESG score had a negative, non-significant estimate, thus suggesting a negative correlation. Thus, an increase in ESG score, when having a low ESG score initially, would lead to a decrease in stock market returns.

Yet, the sensitivity analysis for the second hypothesis showed a statistically significant difference between the high and the low ESG scoring portfolio, despite the low ESG portfolio lacking significance in itself. This result not only showed robust with the inclusion of more variables, but also almost tripled in size, indicating an increasing impact when including trade activity and pollution.

Hypothesis III is an expansion of Hypothesis II, exploring the three separate components of the ESG score; environmental, social and governance. Hence, the third hypothesis assumes that investors weigh the three components differently during their investment decision, given the presence of ambient air pollution. The results from this empirical analysis showed results contradicting the ones from Hypothesis II. Estimates for all three components proved statistically insignificant with a negative direction, thus displaying a negative relationship between the E, S and G scores and the stock return. The estimate for ambient air pollution also lost its significance when included in these models yet remained negative.

Through a sensitivity analysis deconstructed models were constructed, testing the robustness of the results. When excluding both trade activity and air pollution, the estimates for the three components remained statistically insignificant, but changed direction. Thus, going from a negative to a positive relationship with stock market returns. Studying whether there are apparent differences in high versus low scores, showed some significant results, but these seemed inconsistent in direction.

Lastly, Hypothesis IV is a different expansion of Hypothesis II, and is hereby investigating whether the influence of sustainability varies across sectors with the presence of ambient air pollution. This is done through the analysis of ten sectors represented on S&P 500. None of the results showed any statistical significance, but in line with the results of Hypothesis II, showed a positive relationship. Thus, demonstrating a positive relationship between sustainability and stock market returns.

Testing the robustness of the results discovered, the deconstructed models did not alter the estimates' lack of significance nor the positive relationship with stock market returns. However, some statistical significance was found when testing high, low and hedged versions of the ESG estimate for the ten sectors. Like Hypothesis III, there was a lack of consistency in direction of the correlation.

7 Discussion

The discussion will connect empirical results arising from this analysis to findings of other studies as well as presented theories. This will be done through the following five topics: information processing, randomness versus significance, awareness versus unawareness, neglected stocks, asymmetries, and anomalies. These five topics were chosen based upon the empirical results discovered and the applied theory in order to debate key aspects of this thesis. The first topic will discuss information and has ties to both the efficient market hypothesis and Merton's model (1987). The second topic, randomness versus significance, will include a discussion of theory by Harvey, Lui & Zhu (2016) and the discussion of awareness versus unawareness will follow. The third topic, awareness versus unawareness, will include a discussion of limitations to the project. Furthermore, the fourth topic will also make ties to Merton's model (1987) discussing evidence of neglected stocks in the results. Asymmetries will be discussed in the fifth topic and lastly, the discussion will include the concept of risk aversion and conservatism related to the obtained results.

7.1 Information

A key aspect of this thesis is how information is processed and incorporated into the market. Different perspectives on information were presented in the theoretical walk-through. Information processing is important to this thesis and discussion, as investor decision-making is based on a deliberate and unconscious processing of information.

Following Bayes' rule, actors react immediately and efficiently to news. According to the efficient market hypothesis in the strong form, information is instantly incorporated into the prices of the market. Assuming pollution is measured in the market as information, effects hereof should according to preceding theories be seen on same-day stock market returns. The initial analysis of Hypothesis I did show such results. However, once conducting a sensitivity analysis of the pollution variable the two-day lagged estimate became consistently significant, whereas the non-lagged estimate no longer showed any significance. A delayed effect in the market reaction suggests that information is not immediately incorporated, thus opposing the efficient market hypothesis. On the other hand, delayed results are coherent with results derived by Bullinger (1989) suggesting effect delays of up to four days.

Following the same line of thought as above, founded in theory presented by Keef & Roush (2007) as well as Shu & Hung (2009), weather affects stock market returns. Weather information is easily accessible through weather apps, looking through the window and other sources, which then should affect returns on that same day. Results from this analysis shows no statistically significant estimates, which differ from expectations. This could be due to virtual trading and investors not being affected by the same weather conditions if situated at different geographical locations.

Results from Hypothesis II showed that for high ESG scoring companies, an increase in score lead to a positive, statistically significant impact on stock market returns. This would suggest that investors consider the overall ESG score as relevant information in investment decision-making. The low ESG scoring companies had a negative and statistically non-significant estimate suggesting the opposite, that investors do not value this information. Hence, through sensitivity analysis it is found that high scoring companies outperform low scoring companies significantly.

Friede et al (2015) explores the connection between ESG scores and stock market returns through a vast literature review and find a nonnegative correlation between ESG score and return. This relationship between ESG scores and stock market returns are thus coherent with the results found regarding the high scoring as well as the high-minus-low scoring portfolio. Directly opposing the positive relationship between ESG scores and stock market returns is a study conducted by Sodjahin et al (2018). They find a negative correlation for both the high and the low scoring companies.

If investors updated their belief and information was incorporated in the market almost instantly, high ESG scoring companies would not earn an excess return based on this information. A possible behavioural reason for this, could be conservatism bias. This would make investors hold on to their current believes and update these with new information more slowly.

It would be reasonable to assume that given high levels of pollution, investors choose to invest in companies that have a high environmental score, compared to either social or governance parameters. Further expecting investors weighing the scores differently because of changing media attention regarding the three aspects, where the environment is currently widely discussed. Thus, the assumption would be that high scoring environmental portfolios outperform high scoring governance portfolios and high scoring social portfolios. This was investigated in Hypothesis III.

The analysis conducted in this thesis showed that none of the three components are statistically significant and that all three have a negative correlation with stock market returns. Supporting this negative relationship is the study by Sodjahin et al. (2018). They argue that one of the reasons for the negative relationship is the risk mitigating features of the high ESG score and that this is a key component of investor decision-making. The same cannot be concluded for this study as none of the parameters prove to be significant. A lack of statistical significance could suggest that data follows a random walk given by weak form of market efficiency. Friede et al (2015) contests these findings, where the majority of the studies included in the paper finds a positive relationship between the components and corporate financial performance.

The sensitivity analysis in Hypothesis III did indicate that the environmental score has some statically significance in the difference between high and low scores, unlike the social and governance scores. Confirming this result, Limkriangkrai et al. (2017) finds that high environmental and social portfolios outperform low scoring portfolios. However, only the environmental score shows statistical significance. Contradicting Limkriangkrai et al's (2017) finding regarding the social score, this thesis concludes a significant and negative difference, meaning the low portfolio outperforms the high. For both studies the governance scores are negative in difference, but for this thesis not statistically significant.

Processing of information, thus the incorporation of ESG scores into the market, could also be sector specific, which was the main focus of Hypothesis IV. This does however not turn out to be the case through the data analysis, as no sector showed any significant relationship between ESG and return. Halbritter & Dorfleitner (2015) also studied the ESG influence on stock market returns in various sectors. They validate the results found in this thesis, through estimates with no statistical significance.

In the analysis of the last hypothesis it can be argued that it may not be the ESG score itself that contain the essential information for investors to make an investment decision, but rather the comparison it allows investors to make across sectors. This becomes evident through the sensitivity analysis, where some results show significance in the high-minus-low variables, despite no statistical significance in the initial analysis. The lack of significance in both Hypothesis III and IV might also suggest that data follows a random walk as represented in efficient market hypothesis as efficiency in its weak form. Compared to the second hypothesis, it shows an inconsistency in the results from the perspective of the efficient market hypothesis. The inconsistency lies within the underlying hypothesis foundation, where instead of looking at the market as a whole, sectors are analysed individually. Results should cohere and the relationships remain positive but lose their significance.

Another topic related to information is the problem of differentiation between sustainability and transparency. It can be problematic to distinguish between those two concepts when discussing ESG scores, as the score is a combination of both (Spitzer & Mandyck, 2019). This information, however, may not be explicated to investors incorporating the ESG score into their investment decisions. Investors might be of the belief that they invest in the most sustainable companies, when in fact they might be investing in mediocre sustainable although highly transparent companies.

Another aspect is the level of information the ESG score provides the investors. It could be argued that the results found suggest the overall sustainability score is more important to the investors than the individual parameter, although pollution is evident in everyday life. Arguable this result puts further pressure on companies, as they not only need to disclose information of all three parameters with equal priority, but also have the focus internally within the company. Hence, it does not pay off to have a high environmental score, if the social or governance scores are extremely low. What seems pivotal is the overall performance, and thereby overall transparency and disclosure of information. Refuting the importance of the ESG score as a whole is a report from Donnelley Financial Solutions (2018), which states that only 30 percent of investors find company provided ESG information sufficient. On the other hand, the report by Ernest & Young (2017) presents through a survey that only 14 percent of the questioned investors do not find ESG information useful during investment decisions.

Halbritter & Dorfleitner (2015) discusses the importance of the data provider used by the investor. By exploring ESG scores', acquired from different providers, influence on financial performance, they find no statistically significant alpha estimates. Thus, disregarding the provider utilised, ESG scores do not have significant effects on stock market returns. Yet, when investigating the differences among the providers, differences exists. They conclude non-significant differences among the data providers varying in both magnitude and direction. This could suggest a lack of transparency and consistency arising from the competitiveness among providers, which in turn infers obscured comparability.

This would lead to a question of whether the ESG information is used and not significant or simply not used? Halbritter & Dorfleitner (2015) would argue that the confusion arising from the different data providers hinders investors from utilising the ESG scores during investment decision-making. Another argument could be that some investors, as suggested by Donnelley Financial Solutions (2018), do not find ESG information sufficient. Both of these effects could explain the lack of statistically significant results of this thesis.

7.2 Randomness versus Significance

This section will draw lines to Taleb's (2007) concepts of randomness and ergodicity, as well as the paper by Harvey, Lui & Zhu (2016). This will include a discussion of whether the obtained results are, in reality valid, or in part can be contributed to randomness.

In Hypothesis I, $PM_{2.5}$ lagged for two periods and fog proved to be significant variables. The result of a delayed effect of air pollution and weather effects are similar to results from other research papers (Bullinger, 1989; Keller et al., 2005). Through the sensitivity analysis, only snow depth as a one-day lagged variable also showed statistical significance with a negative correlation with stock market returns. Regarding the snow depth variable, one could argue that returns would be higher when snow depth is high, because people are more indoors and therefore arguably trade more. On the other hand, snow usually means cold, wet weather which has a negative impact on investor moods and ultimately lead to lower returns. The question is thus, which effect weights heavier. Such a discussion could be conducted for more of the variables included such as precipitation, wind speed and temperature. As discussed in section 5.2, weather variables influence stock market returns, where positive effects are seen from higher temperatures and negative effects arose from wind and cold (Keef & Roush, 2007; Shu & Hung, 2009; Keller et al., 2005).

However, it raises the question of either omitted variable bias or randomness is at play. According to Taleb's (2007) understanding of ergodicity, some of the results could be random observations, bearing the resemblance of a pattern given the context that it is studied in. This means that if the studied time period would have been longer, the observed pattern would most likely disappear. For example, results discovered in Hypothesis I shows a shift in direction of the $PM_{2.5}$ coefficient from time t to time t-2. Thereby, one pattern substitutes another. This effect is stronger as both results are found statistically significant.

It could also be argued that the sample of companies is too small and narrow. For this reason, we do not wish to generalize our results beyond our sample or time period as this could cause a problem of induction. A problem of induction means that academics are too quick to generalise specific studies, making conclusions on an entire population based on a small sample. This is also closely linked to another concept, Taleb (2007) describes as hindsight bias. He argues that data is studied so hard, researchers “stumble” upon a relationship that might not even be present. Such might especially be true for Hypothesis III and Hypothesis IV, where it can be argued that data is constructed in so many ways that by coincidence some of the regressions should prove significant. For neither of the last two hypotheses none of the results found through the original analysis proved any significance. This finding contradicts the base assumption presented by Taleb (2007).

Another important aspect of the theory is the survivorship bias. Only companies represented on NYSE and S&P 500 were studied. They can be considered survivors, meaning successful companies with a large investor base and consistent earnings. Merely through the characteristics of these companies a bias arises, which may have influenced data collected and thus the empirical results. This bias is further established through the assumption that investors compare companies with other companies on S&P 500, which might, in reality, not be the case. Investors most likely compare companies across various industries, sectors, countries and exchanges, making the investment decision more complex and broader, than the scope of this paper. This is especially evident in Hypothesis IV, where none of the results proved to be statistically significant.

An argument in favour of the results discovered in Hypothesis I and II might be obtained due to datamining and randomness, is the lack of significance in Hypothesis III and IV. Harvey, Lui & Zhu (2016) argue, how in asset pricing and financial modelling, datamining is so common that higher cut-off values should be implemented to reduce the number of false positives. They reason that instead of an absolute t-value of two, the cut-off value should be increased to an absolute value of three. In Table 32 in the appendix, is a display of the t-values of the statistically significant coefficients from the analysis. When evaluating the results based on the cut-off value argued by Harvey, Lui & Zhu (2016), only three estimates would prove statistically significant in explaining stock market fluctuations across all tested estimates.

According to the new cut-off value, none of the results derived from Hypothesis I is significant. However, the t-value of the lagged pollution variable, $PM_{2.5}$, is very close to being significant with a t-value of -2.7210. Therefore, it can be argued that these results still can be applicable in concluding a negative correlation between ambient air pollution and the NYSE Composite Index. This further substantiates the usage of the lagged variable in the additional hypothesis testing. The three estimates which showed statistical significance in accordance with Harvey, Lui & Zhu (2016) were trade activity in both the high (-5.7020) and the low (-5.4240) scoring portfolios, as well as the difference between the high and the low ESG score (4.4410). Fundamentally the findings of the thesis would not change by increasing the cut-off value. The analysis showed through statistically insignificant results of Hypothesis III and IV, that it is the ability to compare companies' ESG scores, rather than the score in itself, which impacts returns.

7.3 Awareness versus Unawareness

This section will discuss the efficient market hypothesis in relation to the analysis in order to question whether the information acquired is processed consciously or unconsciously. When studying the effects of weather and ambient air pollutants, like $PM_{2.5}$, there are studies explaining how effects can be delayed, e.g. Bullinger (1989) who showed effects could lag up to four days. The question thus becomes whether the effect is apparent several days after exposure, because that is when it takes effect in behaviour or because news from the media relating to the pollution levels come out?

In this study it has not been possible to distinguish whether investors were affected by media or environmental impacts, since only pollution values and stock market returns were measured. Thus, it is not possible to distinguish between actual and perceived air pollution as well as awareness and unawareness regarding investment decisions. Assuming complete awareness regarding pollution and as an effect hereof a conscious investment decision made by the investors, the effect found in this study is indeed delayed. Such a result would suggest semi-strong market efficiency, where all publicly available information is reflected in the market. In such a market it would not be possible to obtain excess return without inside information. Whether some investors have a source for this is impossible to know within the scope of this study.

An observation that could speak in favour of a potential perceived versus actual pollution is the statistical significance of the fog variable. This could suggest that fog may be confused with pollution in the air by creating a similar effect through reduced visibility and potentially restrained breathing.

Are the investors then making a conscious investment decision based on the actual pollution levels or the perceived ones, which could have been enhanced by the presence of fog? Although fog proved to be significant in the first hypothesis, it is however not so in the second, and was therefore omitted from the remaining part of the analysis.

Another point of discussion is the geographical location of the investors. It is not possible to obtain information of the geographic location of the traders included in this study. As the vast majority of all stock trading today is done virtually, there is no guarantee that traders trading on NYSE is also located in New York City. This means that investors might not be located in New York City at the time of trading or on high pollution days. Such an insecurity makes it difficult to decide whether investors are influenced by the air pollution in New York City or the city they are located in at the time of trade. Additionally, it also makes it hard to determine whether the reaction towards the increased pollution levels occur due to physical exposure or external information sources.

As described and discussed earlier, the ESG score is not only a representation of the actual degree of sustainability of a company but also the degree of transparency regarding company sustainability. Thus, when an investor is making a conscious, or unconscious, decision of investing in a high scoring company, is it then the transparency or the sustainability he/she is investing in? Considering this train of thought in connection with the social norms introduced by Hong & Kacperczyk (2009), ESG scores might play an important role for investment decisions today but may change tomorrow when the focus of what is acceptable changes. Social acceptance and trends are concepts adhering to behavioural finance, suggesting that despite the investor taking a conscious decision, this decision could be influenced by subconscious effects arising from external sources.

7.4 Neglected Stocks

Following Merton's intuition, there would be a discount on neglected stocks, because investors have less information about them. Therefore, they are traded less frequently, which can give a higher return. The same intuition can be observed in the law of supply and demand. If the price is "cheap" relative to the return, there will be many buyers, creating high trade activity, which will push prices up and ultimately flattening out any obtainable return. Therefore, Merton's model coincides with the law of supply and demand, explained through a different perspective. This would, according to the theory, suggest a negative relationship between trade activity and returns. In other words, the higher the trade activity the lower the expected return and vice versa. Results derived from the analysis of Hypothesis II, III and IV instigate a similar conclusion. All estimates for trade activity have some degree of statistical significance and the vast majority of them are negatively correlated with stock market returns. Despite the minimal size of the estimate, the negative sign suggests that an increase in trade activity will lead to a decrease in stock market returns.

Merton describes neglected stocks as stocks which provide less information and abide a smaller investor base. In this setting, neglected stocks are stocks with low E, S, G or ESG scores as these are considered a measure of sustainability as well as information-transparency regarding sustainable initiatives. Hence, companies with high ESG scores disclose more information, or it is simply easier to obtain information about them, resulting in more investors being aware of them. This could in turn lead to an increase in trade activity, which then lowers the expected return. In relation to this study, it would mean that low ESG scoring portfolios would outperform high scoring portfolios, completely opposing the main assumption of Hypothesis II.

According to Merton (1987), high ESG scoring companies would have negative correlation with stock market returns, due to their magnitude of accessible information and investor awareness. Likewise, low ESG scoring companies would have a positive correlation, caused by a lower degree of available information and thereby a lower awareness among investors. Results, however, show the opposite, with high ESG scoring companies having a positive and significant relationship and vice versa for the low ESG scoring companies. Thus, being consistent with the original statement of Hypothesis II and hereby contradicting Merton's model.

The same is apparent in Hypothesis IV, where all ESG estimates for the ten sectors are positive. With a positive estimate for ESG, an increase in the level of information leads to an increase in stock market returns. Yet, results derived from analysing ESG impact on sectors showed no statistical significance. The results observed in both Hypothesis II and IV is a contradiction of the reasoning behind neglected stocks as defined by Merton (1987).

Nonetheless, Hypothesis III shows a different direction in estimates. All three components of the ESG score display a negative relationship with stock market returns. This is thus in line with the expectations of Merton's model, which suggests that a higher E, S or G score would lead to a reduced return. Yet, results are statistically insignificant for all three parameters of the score, which suggest that the additional information gained by studying the individual components does not contribute to the investor's investment decision.

One reason why some results might show statistical insignificance and others do not, as well as some estimates agreeing, and some refuting Merton could be due to the double-sided meaning of the ESG score. The ESG score is, as mentioned, a combination of information and of sustainability. Merton only accounts for the informational aspect of the ESG through his model. Within the scope of this thesis it is not possible to determine, which part is the most prominent during investment decisions. Thus, results from Hypothesis II and IV argue that it might be the sustainable aspect outweighing the informational aspect and vice versa for the results of Hypothesis III.

7.5 Asymmetries

Asymmetric probabilities paired with asymmetric outcomes leads to volatile expectations and the frequency of the outcome in itself becomes irrelevant. In his book Taleb (2007) discusses the concept of asymmetric probabilities, which describes a situation in which the probability of two or more outcomes are not identical. Additionally, he describes asymmetric outcomes as non-equal payoffs. Asymmetric probabilities are in this project materialised through the high and the low pollution days, meaning that there are significantly fewer high pollution days than low pollution days. Furthermore, the stock market return outcomes arising from ambient air pollution effects are defined as asymmetric outcomes. It is expected that the effect of pollution may not affect investors the same way on high and low pollution days, which in turn might cause different effects on low and high ESG scoring companies.

High and low pollution days are part of the empirical data collected. In recent years pollution levels have decreased considerably in New York City, as described in limitations, which leads to significantly fewer high pollution days. Having asymmetric probabilities can potentially skew outcomes and ultimately results. If there are only very few highly polluted days, are the investors then in reality reacting to pollution or are they responding to the trends of sustainable investment or something completely different? Testing whether ambient air pollution indeed does infer negative movements in stock market returns in Hypothesis I, results showed that it did. The estimate for ambient air pollution, $PM_{2.5}$, was negative and statistically significant at a ten percent level, concluding a negative relationship. This was true for both the immediate and the delayed effect, where the two-days delayed effects showed consistent significance. Identically, Hypothesis II also resulted in statistically significant and negative estimates for the two-days delayed effects of the ambient air pollutant. Based on these results it seems there is no bias ascended from asymmetric probabilities.

Continuing the discussion by further exploring the results of Hypothesis III and IV, none of the analyses showed statistically significant results for pollution, neither main analysis nor sensitivity analysis. Whether this is partly due to asymmetric probabilities and the low frequency of highly polluted days or randomness, as discussed earlier, is hard to determine with certainty based on the scope of this thesis.

Several hypotheses analysed show signs of asymmetric outcomes, arising from the influence of ESG scores on stock market returns. Asymmetric outcomes become evident in the second hypothesis, where the estimate of the low ESG score portfolio proved to be negative, and the high ESG score portfolio positive. Additionally, the low ESG score portfolio estimate was statistically insignificant, whereas the high score portfolio showed significance at a five percent level. Pollution effects were identical in the two portfolios and yet the effects proved very different. Results showed that high scoring companies with an increase in ESG ultimately had a significant effect, increasing stock market returns. Companies with a low ESG score had a negative impact on stock market returns from an increase in ESG score, which was statistically insignificant. Such a result could suggest that investors are naturally drawn to more sustainable companies. However, ultimately through the sensitivity analysis, it was discovered that the high ESG scoring portfolio indeed did outperform the low ESG scoring portfolio with statistical significance.

Another asymmetry transpired from the comparison of the ESG results of Hypothesis II and III. Hypothesis II showed a positive correlation between the high ESG and the hedged ESG and stock market returns, whereas all three components of Hypothesis III showed a negative relationship. Such an asymmetry could arise from information processing as described earlier in the discussion. Through the analysis the ESG score has proven to be mostly used as a tool for comparison rather than a definitive number in itself. When the ESG score gets dissected into its separate components, this is no longer a tool for comparison but indigestible specified information, which investors do not attribute any value to.

The same asymmetry can be seen when comparing the results of Hypothesis III and IV. Each sector analysed in Hypothesis IV displays a positive, but not statistically significant, relationship between ESG score and stock market returns. For the individual sector the complete ESG score could act as a good measure for comparing companies within, but the individual component of the score is too detailed.

7.6 Anomalies

The Li & Peng (2016) study discussed in section 2.3 described how ambient air pollution influences one's mood which in turn manifests itself through pessimism, increased risk aversion and low elasticity of intertemporal substitution. As established through the economic theory, risk aversion is a state where an investor is disinclined to take on risky investments. Earlier it was introduced how sustainable investing is used as a risk mitigator, with special focus on reputational and regulatory risk. Based on these theoretical findings, it would be expected to see a higher degree of trade activity in the high ESG scoring portfolio compared to the low scoring portfolio. This is due to the assumption that a higher score means a higher degree of sustainability and thus a higher degree of risk mitigation. The results of Hypothesis II showed trade activity estimates of 0.0000 and -0.0000 for the high and low scoring portfolio respectively. Thus, indicating there might be a difference in the two estimates, yet they are too small to determine with certainty. Nonetheless, Hypothesis II did conclude, how in terms of stock market returns, the high scoring portfolio outperformed the low scoring portfolio, which can be an indicator of the previously explained correlation.

The report presented by Ernest & Young (2017) shows how the main argument for risk aversion among investors regarding sustainable investment, is the possibility of future regulations of less sustainable companies. If this is the case, higher trade activity would be expected for high scoring companies, which as discussed above, was not apparent. Yet, in terms of stock market returns, the high scoring companies do outperform the low scoring ones. This would then infer that investors are indeed risk averse. The same analysis of Hypothesis II did also show statistical significance of the pollution estimate, which would suggest that pollution might indeed have an impact on stock market returns. One could argue that results imply how investors are in fact risk averse and being affected by air pollution, which might create a higher degree of preference for companies with high sustainability scores. Thus, risk aversion may have a direct effect on the demand and supply of stocks, resulting in less trade activity and higher returns.

Another behavioural concept that could create the same reaction in the market is the conservatism bias. This becomes evident in two ways; a delayed action caused by clinging on to old information, or an overreaction to new information. In the situation where an individual cling to past knowledge, instead of acknowledging newer evidence in their decision-making process, investment decisions do not create immediate reactions in the market. Such an asymmetry would lead to an unobservable bias in data and thus in the results. If for example an investor is holding on to the ESG score of the previous year and trading based on this information, rather than the latest score, his/her trading behaviour would not be utility maximising. Results derived from this investor would not be credible in terms of not being a response to the current information. This type of delayed reaction to ESG scores will make the results of a particular year either seem better or worse than they in actual might be. In case of an overreaction to new information, an investor would foe example see a decrease in ESG scores and immediately sell all held stocks instead of evaluating the new information together with already acquired information. Such form of frenzy skews observed data and results by increasing the volatility. Again, this type of investor behaviour could make yearly results appear better or worse, than they truly would be.

Since it is impossible to know whether investors suffer from a conservatism bias, it is not possible to determine if the data collected has been influenced in such a way. Especially for companies which shifted from high to low or low to high portfolios during the course of the time period in question, conservatism bias could be affecting the results discovered. It is therefore assumed, that the majority of the investors act rationally, and those who do not, will outweigh each other, making results reliable for conclusions.

8 Conclusion

Choosing to investigate the correlations between ambient air pollution, sustainability scoring, and stock market returns arose from the question of conscious choice or environmental effect. Is sustainable investing a conscious choice made by the investors or is it a response to environmental factors. This curiosity manifested itself in a research of how ambient air pollutants in New York City affect investor behaviour and what is the impact on investments in sustainable businesses.

The establishment of four hypotheses created the foundation for the analysis, which was conducted through ordinary least square regressions. Initiating the analysis with a hypothesis being an extension of previous studies, determining the relationship between the ambient air pollutant $PM_{2.5}$ and stock market returns on the NYSE Composite Index. Through this analysis, a negative correlation between air pollution and stock market returns was established. A robustness test of the results showed how the negative effect of $PM_{2.5}$ was lagged by two days, meaning the effect becomes apparent two days after investor exposure. Such a finding is in line with the results of Bullinger (1989), who estimated significant effects up to four days after exposure; as well as Li & Peng (2016), who stated how air pollution negatively impacted stock returns through three separate streams.

Hypothesis I thus established the actual connection between ambient air pollution and stock market returns. Hypothesis II aims to instigate the examination of the sustainability perspective through the inclusion of Bloomberg's ESG scores for 463 S&P 500 companies, testing for differences in high versus low scoring companies. The conclusion from this analysis was that the high ESG scoring portfolio had a statistically significant positive correlation with stock market returns, whereas the low scoring portfolio had a statistically insignificant negative correlation. This conveys, that having a high ESG score makes a difference in terms of stock market returns. Conducting a robustness test of the results showed how the difference (high-minus-low) was significant and positive, meaning the high ESG scoring portfolio outperform the low ESG portfolio. Thus, suggesting how ESG scores are also utilised as a comparison tool when evaluating investment opportunities. Theory presented by Harvey, Lui & Zhu (2016), argues for an increased cut-off value to determine statistical significance. Testing based on this alternative value still showed significance for the high-minus-low estimate, further cementing ESG's role as a tool for comparison.

Finding that the high scoring companies indeed outperformed the low scoring companies contradicts the discussed findings of Merton's (1987) neglected stocks. Through Merton's model a negative correlation between ESG scores and stock returns was expected. Thus, the low ESG scoring portfolio would outperform the high ESG scoring portfolio.

The aim of Hypothesis III was to expand the findings of Hypothesis II by analysing the three ESG components separately. Moving from Hypothesis II to Hypothesis III the direction of the estimates changed, thereby conforming to Merton's thoughts on the influence of information on stock market returns. Nonetheless, it became evident that neither of the three components showed any statistical significance in themselves. This suggests that investors do not add extra value to the individual environmental, social or governance score and the in-depth information provided hereby. As the discussion argues, this could be due to information overload or that investors simply do not value the additional insight provided by the individual components. In the sensitivity analysis the environmental score did however display some significance. A significant and positive estimate for the high-minus-low variable could partly confirm the initial assumption that high pollution may create a higher motivation and natural link to investing in environmentally friendly companies, rather than socially or governance responsible.

Discovering that there is no statistical significance in the individual components themselves (Hypothesis III), but that high ESG scores and the difference in ESG scores (Hypothesis II) do show significant results, Hypothesis IV was thus created. Hypothesis IV aims to examine whether the influence of ESG scores may vary across sectors by studying a total of ten different sectors in S&P 500. All results showed statistical insignificance, meaning that no notable differences across sectors could be observed. Although coefficients across sectors showed minor differences in magnitude, the insignificance made the results unreliable and difficult to interpret with certainty. During the sensitivity analysis, especially among the hedged estimates, mainly positive, statistically significant estimates were found. This infers that it is the difference between high and low scores that impact stock market returns rather than the score itself, and that an increase in ESG score causes a positive effect on stock market returns.

Overall, this thesis can thus conclude that pollution does play a role in investors investment decisions regarding sustainable companies. The effects seen on stock market returns is negative and delayed by two days after investor exposure.

The ESG score as a sustainability measure creates more value as an instrument for company comparison, as the score in itself may not provide sufficient substantial information. When utilising the ESG score as a sustainability proxy, a positive correlation between ambient air pollution, ESG scores and stock market returns are established, indicating how high levels of pollution leads to investing in more sustainable companies.

9 Extension of Research

This section will briefly introduce suggestions for further studies emanating from this thesis. It will contain suggestions regarding geographical location and a predictive study of pollution with a regulatory focus.

As discussed through Taleb's (2007) concept of "the problem with induction", there is no claim to make the conclusion valid for any other than the studied time period with the studied companies. It is acknowledged that the results are partly a product of the historical period, that have been studied with the limitations it included. This study thereby does not make prediction regarding future developments. It could be of interest however, to study which implications pollution would have on the stock market if the level rose or fell further to a new benchmark-level. What would it mean for the returns on the stock market? And would risk aversion increase, creating negative returns? As New York City's pollution level has decreased substantially, it could be of interest to study cities in China, which contain heavily polluted areas (Aqicn, 2019). This would allow for a study of low pollution days versus high pollution days, hereby investigating the marginal differences. It could also be interesting due to social norms, that vary between cultures and geography, perhaps creating different investment behaviours.

The results of this thesis show high degrees of inconsistency in regard to statistical significance of the ESG estimates. Halbritter & Dorfleitner (2015) argues that results are very provider dependent, which could explain this inconsistency. Thereby, suggesting that utilizing data provider could infer different results. The variety of ESG data providers paired with the provider dependency, could cause a lack of transparency to investors utilising this information. Based on this, a predictive study of possible regulatory effects on lack of transparency could be conducted.

The European Union is planning to make a framework for creating a system to "rate ratings" within sustainability. Meaning a system that would evaluate the different sustainability scoring systems to each other. A suggestion for further research could thereby be, how this framework could change the informational value the various ESG scores provide. (K.K., 2018) Through validation of the EU, are some companies then more attractive to investors? Will this political reassurance create a higher degree of transparency that would influence the investment decision? And could this framework remove some potential confusion between transparency and sustainability related to the ESG score?

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11 Appendix

Table 23 - Results on Daily NYSE Stock Returns from Several Lags of Air Pollution (pct.)

	Daily	1-day lag	2-day lag	3-day lag	4-day lag
$PM_{2.5t}$	0.0135*	0.0138*	0.0107	0.0106	0.0108
$PM_{2.5t-1}$		-0.0005	0.0081	0.0069	0.0069
$PM_{2.5t-2}$			-0.0181**	-0.0147*	-0.0145*
$PM_{2.5t-3}$				-0.0076	-0.0076
$PM_{2.5t-4}$					0.0009

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 24 - Results on Daily Weather Variables from Several Lags (pct.)

	Daily	1-day lag	2-day lag	3-day lag	4-day lag
$Temperature_t$	0.0038	0.0055	0.0057	0.0058	0.0052
$Temperature_{t-1}$		-0.0018	-0.0001	-0.0002	-0.0005
$Temperature_{t-2}$			-0.0023	-0.0020	-0.0018
$Temperature_{t-3}$				-0.0004	-0.0046
$Temperature_{t-4}$					0.0059
	Daily	1-day lag	2-day lag	3-day lag	4-day lag
$Dew\ Point_t$	-0.0038	-0.0018	-0.0020	-0.0018	-0.0026
$Dew\ Point_{t-1}$		-0.0036	-0.0022	-0.0022	-0.0023
$Dew\ Point_{t-2}$			-0.0023	-0.0013	-0.0011
$Dew\ Point_{t-3}$				-0.0017	-0.0046
$Dew\ Point_{t-4}$					0.0047
	Daily	1-day lag	2-day lag	3-day lag	4-day lag
$Air\ Pressure_t$	0.0016	-0.0014	-0.0013	-0.0018	-0.0016
$Air\ Pressure_{t-1}$		0.0055	0.0049	0.0060	0.0061

Air Pressure$_{t-2}$			0.0011	-0.0019	-0.0025
Air Pressure$_{t-3}$				0.0057	0.0075*
Air Pressure$_{t-4}$					-0.0034
	Daily	1-day lag	2-day lag	3-day lag	4-day lag
Visibility$_{t}$	0.0203	0.0194	0.0195	0.0195	0.0212
Visibility$_{t-1}$		0.0074	0.0042	0.0037	0.0046
Visibility$_{t-2}$			0.0135	0.0155	0.0152
Visibility$_{t-3}$				-0.0095	-0.0092
Visibility$_{t-4}$					-0.0014
	Daily	1-day lag	2-day lag	3-day lag	4-day lag
Wind Speed$_{t}$	0.0049	0.0049	0.0048	0.0049	0.0050
Wind Speed$_{t-1}$		-0.0000	0.0000	0.0011	0.0011
Wind Speed$_{t-2}$			-0.0006	-0.0030	-0.0024
Wind Speed$_{t-3}$				0.0091	0.0074
Wind Speed$_{t-4}$					0.0067
	Daily	1-day lag	2-day lag	3-day lag	4-day lag
Precipitation$_{t}$	-0.0047	-0.0022	-0.0024	-0.0035	-0.0009
Precipitation$_{t-1}$		-0.0374	-0.0371	-0.0406	-0.0389
Precipitation$_{t-2}$			-0.0033	0.0009	0.0066
Precipitation$_{t-3}$				-0.0505	-0.0572
Precipitation$_{t-4}$					0.0819
	Daily	1-day lag	2-day lag	3-day lag	4-day lag
Snow Depth$_{t}$	-0.0098	0.0193	0.0173	0.0189	0.0245
Snow Depth$_{t-1}$		-0.0377	-0.0578*	-0.0587*	-0.0677**
Snow Depth$_{t-2}$			0.0281	0.0325	0.0391
Snow Depth$_{t-3}$				-0.0063	0.0271
Snow Depth$_{t-4}$					-0.465*

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 25 - Sensitivity Analysis of $PM_{2.5}$

	No other variables	**No weather variables**	**Only $PM_{2.5}$ and Fog**
$PM_{2.5,t}$	0.0103*	0.0104*	0.0112*

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 26 - Sensitivity Analysis of High-Minus-Low ESG

	No other variables	**No air pollution**	**Full model**
ESG score, ESG_t^{H-L}	0.0054*	0.0152***	0.0150***

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 27 - Sensitivity Analysis of Fog Significance in Hypothesis II

Variable	**Estimate (%)**	**P-value**
Panel A		
ESG score, ESG_t^H	0.0025*	0.0611
Trade activity, v_t^H	-0.0000***	0.0000
$PM_{2.5,t-2}$	-0.0056*	0.0645
Fog	-0.0425	0.1632
Constant	0.1776*	0.0840
Panel B		
ESG score, ESG_t^L	-0.0026	0.2758

Trade activity, v_t^L	-0.0000***	0.0000
$PM_{2.5,t-2}$	-0.0065**	0.0339
Fog	-0.0364	0.2314
Constant	0.3938***	0.0015

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 28 - Sensitivity Analysis of E, S and G Scores

	No other variables	**No air pollution**	**Full model**
E score, E_t	0.0037	-0.0040	-0.0040
S score, S_t	0.0016	-0.0000	-0.0000
G score, G_t	0.0042	-0.0048	-0.0044

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 29 - Sensitivity Analysis for High-Minus-Low E, S and G Scores

	No other variables	**No air pollution**	**Full model**
Panel A			
High E score, E_t^H	0.0026	0.0023	0.0024
Low E score, E_t^L	0.0046	-0.0253***	-0.0250***
HML E score, E_t^{H-L}	0.0043	0.0115***	0.0123***
Panel B			

High S score, S_t^H	0.0022	0.0016	0.0017
Low S score, S_t^L	0.0012	-0.0009	-0.0009
HML S score, S_t^{H-L}	-0.0028	-0.0068***	-0.0069***
Panel C			
High G score, G_t^H	-0.0101	-0.0438	-0.0428**
Low G score, G_t^L	0.0037	-0.0018	-0.0017
HML G score, G_t^{H-L}	-0.0063	-0.0071	-0.0074

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 30 - Sensitivity Analysis of the Ten Sector Scores

	No other variables	**No air pollution**	**Full model**
Communication, ESG_t^{com}	0.0024	0.0034	0.0033
Consumer Discretionary, ESG_t^{CD}	0.0024	0.0002	0.0003
Consumer Staples, ESG_t^{CD}	0.0028	0.0011	0.0010
Energy, ESG_t^{nrg}	0.0027	0.0024	0.0024
Financials, ESG_t^{fin}	0.0021	0.0027	0.0028
Health Care, ESG_t^{HC}	0.0026	0.0025	0.0026
Industrials, ESG_t^{ind}	0.0027	0.0001	0.0001

Materials, ESG_t^{mat}	0.0019	0.0020	0.0020
Technology, ESG_t^{tech}	0.0026	0.0006	0.0006
Utilities, ESG_t^{uti}	0.0018	0.0001	0.0001

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 31 - Sensitivity Analysis for High-Minus-Low for Ten Sectors

	No other variables	**No air pollution**	**Full model**
Panel A			
High communications, $ESG_t^{H,com}$	0.0016	0.0027	0.0026
Low communications, $ESG_t^{L,com}$	0.0034	0.0023	0.0024
HML communications, $ESG_t^{H-L,com}$	-0.0120	-0.0067	-0.0073
Panel B			
High consumer discretionary, $ESG_t^{H,CD}$	0.0026	0.0045	0.0050*
Low consumer discretionary, $ESG_t^{L,CD}$	0.0019	-0.0091**	-0.0090**
HML consumer discretionary, $ESG_t^{H-L,CD}$	0.0166*	0.0290*	0.0310**
Panel C			

High consumer staples, $ESG_t^{H,CS}$	0.0050	0.0003	-0.0000
Low consumer staples, $ESG_t^{L,CS}$	0.0016	0.0024	0.0026
HML consumer staples, $ESG_t^{H-L,CS}$	0.0024	0.0033	0.0025
Panel D			
High energy, $ESG_t^{H,nrg}$	0.0021	0.0024	0.0023*
Low energy, $ESG_t^{L,nrg}$	0.0032	0.0013	0.0013
HML energy, $ESG_t^{H-L,nrg}$	0.0037	0.0038	0.0036
Panel E			
High financial, $ESG_t^{H,fin}$	0.0016	0.0024*	0.0025*
Low financial, $ESG_t^{L,fin}$	0.0025	0.0007	0.0008
HML financial, $ESG_t^{H-L,fin}$	0.0037	0.0060**	0.0062**
Panel F			
High health care, $ESG_t^{H,HC}$	0.0022	0.0029*	0.0029*
Low health care, $ESG_t^{L,HC}$	0.0028	0.0027	0.0027
HML health care, $ESG_t^{H-L,HC}$	0.0048	0.0095***	0.0095***

Panel G			
High industrial, $ESG_t^{H,ind}$	0.0024	0.0050***	0.0052***
Low industrial, $ESG_t^{L,ind}$	0.0026	-0.0077**	-0.0075**
HML industrial, $ESG_t^{H-L,ind}$	0.0078**	0.0100	0.0100
Panel H			
High material, $ESG_t^{H,mat}$	0.0018	0.0029**	0.0028**
Low material, $ESG_t^{L,mat}$	0.0019	-0.0005	-0.0005
HML material, $ESG_t^{H-L,mat}$	0.0044	0.0064*	0.0060*
Panel I			
High technology, $ESG_t^{H,tech}$	0.0025	0.0029	0.0030
Low technology, $ESG_t^{L,tech}$	0.0016	-0.0064	-0.0061
HML technology, $ESG_t^{H-L,tech}$	0.0080**	0.0141***	0.0145***
Panel J			
High utilities, $ESG_t^{H,uti}$	0.0018	0.0005	0.0004
Low utilities, $ESG_t^{L,uti}$	0.0018	0.0003	0.0003
HML utilities, $ESG_t^{H-L,uti}$	0.0133**	0.0133**	0.0127**

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

Table 32 - T-Values for Significant Estimates

	Estimate (%)	**T-value**
Panel A		
PM2.5, $PM_{2.5,t}$	0.0135**	1.9260
Fog, F_t	0.1682**	2.4260
2-day lagged PM2.5, $PM_{(2.5,t-2)}$	-0.0181**	-2.7210
Panel B		
High ESG score, ESG_t^H	0.0027**	2.0140
High trade, v_t^H	-0.0000***	-5.7020
2-day lagged PM2.5, $PM_{(2.5,t-2)}$	-0.0055*	1.8120
Low ESG score, ESG_t^L	-0.0025	-1.0230
Low trade, v_t^L	-0.0000***	-5.4240
2-day lagged PM2.5, $PM_{(2.5,t-2)}$	-0.0064**	2.0890
HML ESG, ESG_t^{H-L}	0.0150**	4.4410

Notes: All estimate values are indicated in percentage in order to overcome magnitude differences in regression variables. The p-value for the model is recorded, and * denotes statistical significance of 10%, ** denotes statistical significance of 5% and *** denotes statistical significance of 1%.

R code

Data Description

Unit root test of NYSE daily stock return

```
#Visually, no trend seem to be present in either data series.
#Yet, we test it using a Dickey-Fuller test. We test for the presence of a unit root.
adf.test(Log_return, alternative = c("stationary", "explosive"), k = 0)
```

Unit root test of average stock return for 463 included companies

```
#First we have to plot the average return in order to test for trends
ggplot(Til_regressioner_2, aes(Til_regressioner_2$Date, Til_regressioner_2$`Average return`)) +
  geom_line() + xlab("Date") + ylab("Average Return")
```

```
#Visually there seems to be no trend in the return data.
#Yet, we test for the presence of a unit root, using a Dickey-Fuller test
adf.test(Avg_return, alternative = c("stationary", "explosive"), k = 0)
```

Hypothesis I

Regression

```
#Full model and summary
model.1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                January + Monday, data = Actual_Data)
stargazer(model.1, type = "text")
```

Testing lagged $PM_{2.5}$ values for significance (only showing no lag and 1 lag below)

```
#Building models, where I alter the lag of PM2.5 to see, if all effects are significant
model.pmt <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                  Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                  January + Monday, data = Actual_Data)
stargazer(model.pmt, type = "text") ; summary(model.pmt)
#(+)PM2.5 is significant at 5% and (+)fog is significant at 5%.

model.pmt_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + PM2.5_1L + Temperature +
                    Dew_point + Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth +
                    Fog + Haze + January + Monday, data = Actual_Data)
stargazer(model.pmt_1, type = "text") ; summary(model.pmt_1)
#(+)PM2.5 is significnat at 10% (+)fog is significant at 5%.
```

Testing lagged weather variables for significance (only showing no lag and 1 lag below)

```r
#Building models, where I alter the lag of temperature to see, if all effects are significant
model.temp <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                 Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                 January + Monday, data = Actual_Data)
summary(model.temp)
#(+)temperature is not significant.

model.temp_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature +
                  Actual_Data$`Temperature 1L`  + Dew_point + Air_pressure + Visibility +
                   Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                   January + Monday, data = Actual_Data)
summary(model.temp_1)
#(+)temperature and (-)temperature 1L are not significant.

#Building models, where I alter the lag of dew point to see, if all effects are significant
model.dewp <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                 Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                 January + Monday, data = Actual_Data)
summary(model.dewp)
#(-)dew point is not significant.

model.dewp_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                   Actual_Data$`Dew Point 1L` + Air_pressure + Visibility + Wind_speed +
                   Precipitation + Snow_depth + Fog + Haze + January + Monday, data = Actual_Data)
summary(model.dewp_1)
#(-)dew point and (-)dew point 1L are not significant.
```

```r
#Building models, where I alter the lag of air pressure to see, if all effects are significant
model.airp <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                 Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                 January + Monday, data = Actual_Data)
summary(model.airp)
#(+)air pressure is not significant.

model.airp_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                 Air_pressure + Actual_Data$`Air Pressure 1L` + Visibility + Wind_speed +
                 Precipitation + Snow_depth + Fog + Haze + January + Monday, data = Actual_Data)
summary(model.airp_1)
#(-)air pressure and (+)air pressure 1L are not significant.
```

```r
#Building models, where I alter the lag of visibility to see, if all effects are significant
model.vis <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                 Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                 January + Monday, data = Actual_Data)
summary(model.vis)
#(+)visibility is not significant.

model.vis_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                Air_pressure + Visibility + Actual_Data$`Visibility 1L` + Wind_speed +
                Precipitation + Snow_depth + Fog + Haze + January + Monday, data = Actual_Data)
summary(model.vis_1)
#(+)visibility and (+)visibility 1L are not significant.
```

```
#Building models, where I alter the lag of wind speed to see, if all effects are significant
model.wisp <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                 Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                 January + Monday, data = Actual_Data)
summary(model.wisp)
#(+)wind speed is not significant.

model.wisp_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                   Air_pressure + Visibility + Wind_speed + Actual_Data$`Wind Speed 1L` +
                   Precipitation + Snow_depth + Fog + Haze + January + Monday, data = Actual_Data)
summary(model.wisp_1)
#(+)wind speed and (-)wind speed 1L are not significant.

#Building models, where I alter the lag of precipitation to see, if all effects are significant
model.pre <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                   Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                   January + Monday, data = Actual_Data)
summary(model.pre)
#(-)precipitation is not significant.

model.pre_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                  Air_pressure + Visibility + Wind_speed + Precipitation +
                  Actual_Data$`Precipitation 1L` + Snow_depth + Fog + Haze + January + Monday,
                  data = Actual_Data)
summary(model.pre_1)
#(-)precipitation and (-)precipitation 1L are not significant.
```

```
#Building models, where I alter the lag of snow depth to see, if all effects are significant
model.snd <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                  Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth + Fog + Haze +
                  January + Monday, data = Actual_Data)
summary(model.snd)
#(-)snow depth is not significant.

model.snd_1 <- lm(Log_return ~ Log_return_1L + Log_return_2L + PM2.5 + Temperature + Dew_point +
                  Air_pressure + Visibility + Wind_speed + Precipitation + Snow_depth +
                  Actual_Data$`Snow Depth 1L` +  Fog + Haze + January + Monday, data = Actual_Data)
summary(model.snd_1)
#(+)snow depth and (-)snow depth 1L are not significant.
```

Sensitivity analysis

```
##Sensitivity analysis for PM2.5
#Including only the independent variable PM2.5
summary(lm(Log_return ~ PM2.5, data = Actual_Data))
#PM2.5 is significant at 10% (estimate is 0.0103%)

#Including everything execpt the weather variables
summary(lm(Log_return ~ PM2.5 + January + Monday, data = Actual_Data))
#PM2.5 is significant at 10% (estimate is 0.0104%)

#Only including what was significant in the original model
summary(lm(Log_return ~ PM2.5 + Fog, data = Actual_Data))
#PM2.5 is significant at 10% (estimate is 0.0112%)
```

Hypothesis II

Regressions

```
#Full regression on high ESG
model.3.1 <- lm(Avg_return ~ High_ESG + High_trade + PM2.5_2L, data = Til_regressioner_2)
stargazer(model.3.1, type = "text")
summary(model.3.1)
#High ESG is significant at 5%, high trade is significant at 1% and PM2.5 2L is significant at 10%.
```

```
#Full regression on low ESG
model.3.2 <- lm(Avg_return ~ Low_ESG + Low_trade + PM2.5_2L, data = Til_regressioner_2)
stargazer(model.3.2, type = "text")
summary(model.3.2)
#Low trade and constant is significant at 1% and pm2.5 2L is significant at 5%.
```

Sensitivity analysis

```
##Hedged portfolio
hml_ESG <- High_ESG - Low_ESG
hml_trade <- High_trade - Low_trade
hml_return <- High_return - Low_return
model.hml <- lm(Avg_return ~ hml_ESG + hml_trade + PM2.5_2L, data = Til_regressioner_2)
stargazer(model.hml, type = "text")
summary(model.hml)
```

```
#Sensitivity analysis
summary(lm(Avg_return ~ hml_ESG, data = Til_regressioner_2))
summary(lm(Avg_return ~ hml_ESG + hml_trade, data = Til_regressioner_2))
summary(lm(Avg_return ~ hml_ESG + hml_trade + PM2.5_2L, data = Til_regressioner_2))
```

```
#Including Fog in high ESG
model.4.1 <- lm(Avg_return ~ High_ESG + High_trade + PM2.5_2L + Fog, data = Til_regressioner_2)
stargazer(model.4.1, type = "text")
summary(model.4.1)
#High ESG, PM2.5 2L and constant is significant at 10% and high trade is significant at 1%.
```

```
#Including Fog in low ESG
model.4.2 <- lm(Avg_return ~ Low_ESG + Low_trade + PM2.5_2L + Fog, data = Til_regressioner_2)
stargazer(model.4.2, type = "text")
summary(model.4.2)
#PM2.5 2L is significant at 5% and low trade and constant is significant at 1%.
```

Hypothesis III

Regressions

```
#Full regression on E score
model.3.3 <- lm(Avg_return_hyp3 ~ Avg_E + Avg_trade_E + PM2.5_2L_hyp3, data = Til_regressioner_3)
stargazer(model.3.3, type = "text")
summary(model.3.3)
#Trade and constant is significant at 1%.
```

```
#Full regression on S score
model.3.4 <- lm(Avg_return_hyp3 ~ Avg_S + Avg_trade_S + PM2.5_2L_hyp3, data = Til_regressioner_3)
stargazer(model.3.4, type = "text")
summary(model.3.4)
#Trade and constant is significant at 1%.
```

```
#Full regression on G score
model.3.5 <- lm(Avg_return_hyp3 ~ Avg_G + Avg_trade_G + PM2.5_2L_hyp3, data = Til_regressioner_3)
stargazer(model.3.5, type = "text")
summary(model.3.5)
#Trade is significant at 1%.
```

Sensitivity analysis

```
#Testing interim models for E
model.1.3 <- lm(Avg_return_hyp3 ~ Avg_E, data = Til_regressioner_3)
stargazer(model.1.3, type = "text")
model.2.3 <- lm(Avg_return_hyp3 ~ Avg_E + Avg_trade_E, data = Til_regressioner_3)
stargazer(model.2.3, type = "text")
model.3.4 <- lm(Avg_return_hyp3 ~ Avg_S + Avg_trade_S + PM2.5_2L_hyp3, data = Til_regressioner_3)
stargazer(model.3.4, type = "text")

#Testing interim models for S
model.1.4 <- lm(Avg_return_hyp3 ~ Avg_S, data = Til_regressioner_3)
stargazer(model.1.4, type = "text")
model.2.4 <- lm(Avg_return_hyp3 ~ Avg_S + Avg_trade_S, data = Til_regressioner_3)
stargazer(model.2.4, type = "text")
model.3.4 <- lm(Avg_return_hyp3 ~ Avg_S + Avg_trade_S + PM2.5_2L_hyp3, data = Til_regressioner_3)
stargazer(model.3.4, type = "text")

#Testing interim models for G
model.1.5 <- lm(Avg_return_hyp3 ~ Avg_G, data = Til_regressioner_3)
stargazer(model.1.5, type = "text")
model.2.5 <- lm(Avg_return_hyp3 ~ Avg_G + Avg_trade_G, data = Til_regressioner_3)
stargazer(model.2.5, type = "text")
model.3.5 <- lm(Avg_return_hyp3 ~ Avg_G + Avg_trade_G + PM2.5_2L_hyp3, data = Til_regressioner_3)
stargazer(model.3.5, type = "text")
```

```r
#Testing high vs low for E
model.1.3h <- lm(Avg_return_hyp3 ~ High_E, data = Til_regressioner_3)
summary(model.1.3h)
model.2.3h <- lm(Avg_return_hyp3 ~ High_E + High_trade_E, data = Til_regressioner_3)
summary(model.2.3h)
model.3.3h <- lm(Avg_return_hyp3 ~ High_E + High_trade_E + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.3h)
model.1.3l <- lm(Avg_return_hyp3 ~ Low_E, data = Til_regressioner_3)
summary(model.1.3l)
model.2.3l <- lm(Avg_return_hyp3 ~ Low_E + Low_trade_E, data = Til_regressioner_3)
summary(model.2.3l)
model.3.3l <- lm(Avg_return_hyp3 ~ Low_E + Low_trade_E + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.3l)
model.1.3hml <- lm(Avg_return_hyp3 ~ Hml_E, data = Til_regressioner_3)
summary(model.1.3hml)
model.2.3hml <- lm(Avg_return_hyp3 ~ Hml_E + hml_trade_E, data = Til_regressioner_3)
summary(model.2.3hml)
model.3.3hml <- lm(Avg_return_hyp3 ~ Hml_E + hml_trade_E + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.3hml)

#Testing high vs low for S
model.1.4h <- lm(Avg_return_hyp3 ~ High_S, data = Til_regressioner_3)
summary(model.1.4h)
model.2.4h <- lm(Avg_return_hyp3 ~ High_S + High_trade_S, data = Til_regressioner_3)
summary(model.2.4h)
model.3.4h <- lm(Avg_return_hyp3 ~ High_S + High_trade_S + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.4h)
model.1.4l <- lm(Avg_return_hyp3 ~ Low_S, data = Til_regressioner_3)
summary(model.1.4l)
model.2.4l <- lm(Avg_return_hyp3 ~ Low_S + Low_trade_S, data = Til_regressioner_3)
summary(model.2.4l)
model.3.4l <- lm(Avg_return_hyp3 ~ Low_S + Low_trade_S + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.4l)
model.1.4hml <- lm(Avg_return_hyp3 ~ Hml_S, data = Til_regressioner_3)
summary(model.1.4hml)
model.2.4hml <- lm(Avg_return_hyp3 ~ Hml_S + hml_trade_S, data = Til_regressioner_3)
summary(model.2.4hml)
model.3.4hml <- lm(Avg_return_hyp3 ~ Hml_S + hml_trade_S + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.4hml)

#Testing high vs low for G
model.1.5h <- lm(Avg_return_hyp3 ~ High_G, data = Til_regressioner_3)
summary(model.1.5h)
model.2.5h <- lm(Avg_return_hyp3 ~ High_G + High_trade_G, data = Til_regressioner_3)
summary(model.2.5h)
model.3.5h <- lm(Avg_return_hyp3 ~ High_G + High_trade_G + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.5h)
model.1.5l <- lm(Avg_return_hyp3 ~ Low_G, data = Til_regressioner_3)
summary(model.1.5l)
model.2.5l <- lm(Avg_return_hyp3 ~ Low_G + Low_trade_G, data = Til_regressioner_3)
summary(model.2.5l)
model.3.5l <- lm(Avg_return_hyp3 ~ Low_G + Low_trade_G + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.5l)
model.1.5hml <- lm(Avg_return_hyp3 ~ Hml_G, data = Til_regressioner_3)
summary(model.1.5hml)
model.2.5hml <- lm(Avg_return_hyp3 ~ Hml_G + hml_trade_G, data = Til_regressioner_3)
summary(model.2.5hml)
model.3.5hml <- lm(Avg_return_hyp3 ~ Hml_G + hml_trade_G + PM2.5_2L_hyp3, data = Til_regressioner_3)
summary(model.3.5hml)
```

Hypothesis IV

Regressions

```
#Full model on communications
model.3.6 <- lm(Avg_return_hyp4 ~ ESG_com + Trade_com + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.6)
```

```
#Full model on consumer discretionary
model.3.7 <- lm(Avg_return_hyp4 ~ ESG_CD + Trade_CD + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.7)
```

```
#Full model on consumer staples
model.3.8 <- lm(Avg_return_hyp4 ~ ESG_CS + Trade_CS + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.8)
```

```
#Full model on energy
model.3.9 <- lm(Avg_return_hyp4 ~ ESG_nrg + Trade_nrg + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.9)
```

```
#Full model on financials
model.3.10 <- lm(Avg_return_hyp4 ~ ESG_fin + Trade_fin + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.10)
```

```
#Full model on health care
model.3.11 <- lm(Avg_return_hyp4 ~ ESG_HC + Trade_HC + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.11)
```

```
#Full model on industrials
model.3.12 <- lm(Avg_return_hyp4 ~ ESG_ind + Trade_ind + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.12)
```

```
#Full model on materials
model.3.13 <- lm(Avg_return_hyp4 ~ ESG_mat + Trade_mat + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.13)
```

```
#Full model on technology
model.3.14 <- lm(Avg_return_hyp4 ~ ESG_tech + Trade_tech + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.14)
```

```
#Full model on utilities
model.3.15 <- lm(Avg_return_hyp4 ~ ESG_uti + Trade_uti + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.15)
```

Sensitivity analysis

```
#Testing interim models for communications
model.1.6 <- lm(Avg_return_hyp4 ~ ESG_com, data = Til_regressioner_4)
summary(model.1.6)
model.2.6 <- lm(Avg_return_hyp4 ~ ESG_com + Trade_com, data = Til_regressioner_4)
summary(model.2.6)
model.3.6 <- lm(Avg_return_hyp4 ~ ESG_com + Trade_com + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.6)
```

```
#Testing interim models for consumer discretionary
model.1.7 <- lm(Avg_return_hyp4 ~ ESG_CD, data = Til_regressioner_4)
summary(model.1.7)
model.2.7 <- lm(Avg_return_hyp4 ~ ESG_CD + Trade_CD, data = Til_regressioner_4)
summary(model.2.7)
model.3.7 <- lm(Avg_return_hyp4 ~ ESG_CD + Trade_CD + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.7)
```

```
#Testing interim models for consumer staples
model.1.8 <- lm(Avg_return_hyp4 ~ ESG_CS, data = Til_regressioner_4)
summary(model.1.8)
model.2.8 <- lm(Avg_return_hyp4 ~ ESG_CS + Trade_CS, data = Til_regressioner_4)
summary(model.2.8)
model.3.8 <- lm(Avg_return_hyp4 ~ ESG_CS + Trade_CS + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.8)
```

```
#Testing interim models on energy
model.1.9 <- lm(Avg_return_hyp4 ~ ESG_nrg, data = Til_regressioner_4)
summary(model.1.9)
model.2.9 <- lm(Avg_return_hyp4 ~ ESG_nrg + Trade_nrg, data = Til_regressioner_4)
summary(model.2.9)
model.3.9 <- lm(Avg_return_hyp4 ~ ESG_nrg + Trade_nrg + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.9)
```

```
#Testing interim models on financials
model.1.10 <- lm(Avg_return_hyp4 ~ ESG_fin, data = Til_regressioner_4)
summary(model.1.10)
model.2.10 <- lm(Avg_return_hyp4 ~ ESG_fin + Trade_fin, data = Til_regressioner_4)
summary(model.2.10)
model.3.10 <- lm(Avg_return_hyp4 ~ ESG_fin + Trade_fin + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.10)
```

```
#Testing interim models on health care
model.1.11 <- lm(Avg_return_hyp4 ~ ESG_HC, data = Til_regressioner_4)
summary(model.1.11)
model.2.11 <- lm(Avg_return_hyp4 ~ ESG_HC + Trade_HC, data = Til_regressioner_4)
summary(model.2.11)
model.3.11 <- lm(Avg_return_hyp4 ~ ESG_HC + Trade_HC + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.11)
```

```
#Testing interim models on industrials
model.1.12 <- lm(Avg_return_hyp4 ~ ESG_ind, data = Til_regressioner_4)
summary(model.1.12)
model.2.12 <- lm(Avg_return_hyp4 ~ ESG_ind + Trade_ind, data = Til_regressioner_4)
summary(model.2.12)
model.3.12 <- lm(Avg_return_hyp4 ~ ESG_ind + Trade_ind + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.12)
```

```r
#Testing interim models on materials
model.1.13 <- lm(Avg_return_hyp4 ~ ESG_mat, data = Til_regressioner_4)
summary(model.1.13)
model.2.13 <- lm(Avg_return_hyp4 ~ ESG_mat + Trade_mat, data = Til_regressioner_4)
summary(model.2.13)
model.3.13 <- lm(Avg_return_hyp4 ~ ESG_mat + Trade_mat + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.13)
```

```r
#Testing interim models on technology
model.1.14 <- lm(Avg_return_hyp4 ~ ESG_tech, data = Til_regressioner_4)
summary(model.1.14)
model.2.14 <- lm(Avg_return_hyp4 ~ ESG_tech + Trade_tech, data = Til_regressioner_4)
summary(model.2.14)
model.3.14 <- lm(Avg_return_hyp4 ~ ESG_tech + Trade_tech + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.14)
```

```r
#Testing interim models on utilities
model.1.15 <- lm(Avg_return_hyp4 ~ ESG_uti, data = Til_regressioner_4)
summary(model.1.15)
model.2.15 <- lm(Avg_return_hyp4 ~ ESG_uti + Trade_uti, data = Til_regressioner_4)
summary(model.2.15)
model.3.15 <- lm(Avg_return_hyp4 ~ ESG_uti + Trade_uti + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.15)
```

```r
#Testing high versus low for communications
model.1.6h <- lm(Avg_return_hyp4 ~ High_ESG_com, data = Til_regressioner_4)
summary(model.1.6h)
model.2.6h <- lm(Avg_return_hyp4 ~ High_ESG_com + High_trade_com, data = Til_regressioner_4)
summary(model.2.6h)
model.3.6h <- lm(Avg_return_hyp4 ~ High_ESG_com + High_trade_com + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.6h)
model.1.6l <- lm(Avg_return_hyp4 ~ Low_ESG_com, data = Til_regressioner_4)
summary(model.1.6l)
model.2.6l <- lm(Avg_return_hyp4 ~ Low_ESG_com + Low_trade_com, data = Til_regressioner_4)
summary(model.2.6l)
model.3.6l <- lm(Avg_return_hyp4 ~ Low_ESG_com + Low_trade_com + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.6l)
model.1.6hml <- lm(Avg_return_hyp4 ~ hml_ESG_com, data = Til_regressioner_4)
summary(model.1.6hml)
model.2.6hml <- lm(Avg_return_hyp4 ~ hml_ESG_com + hml_trade_com, data = Til_regressioner_4)
summary(model.2.6hml)
model.3.6hml <- lm(Avg_return_hyp4 ~ hml_ESG_com + hml_trade_com + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.6hml)
```

```r
#Testing high versus low for conusmer discretionary
model.1.7h <- lm(Avg_return_hyp4 ~ High_ESG_CD, data = Til_regressioner_4)
summary(model.1.7h)
model.2.7h <- lm(Avg_return_hyp4 ~ High_ESG_CD + High_trade_CD, data = Til_regressioner_4)
summary(model.2.7h)
model.3.7h <- lm(Avg_return_hyp4 ~ High_ESG_CD + High_trade_CD + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.7h)
model.1.7l <- lm(Avg_return_hyp4 ~ Low_ESG_CD, data = Til_regressioner_4)
summary(model.1.7l)
model.2.7l <- lm(Avg_return_hyp4 ~ Low_ESG_CD + Low_trade_CD, data = Til_regressioner_4)
summary(model.2.7l)
model.3.7l <- lm(Avg_return_hyp4 ~ Low_ESG_CD + Low_trade_CD + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.7l)
model.1.7hml <- lm(Avg_return_hyp4 ~ hml_ESG_CD, data = Til_regressioner_4)
summary(model.1.7hml)
model.2.7hml <- lm(Avg_return_hyp4 ~ hml_ESG_CD + hml_trade_CD, data = Til_regressioner_4)
summary(model.2.7hml)
model.3.7hml <- lm(Avg_return_hyp4 ~ hml_ESG_CD + hml_trade_CD + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.7hml)
```

```r
#Testing high versus low for consumer staples
model.1.8h <- lm(Avg_return_hyp4 ~ High_ESG_CS, data = Til_regressioner_4)
summary(model.1.8h)
model.2.8h <- lm(Avg_return_hyp4 ~ High_ESG_CS + High_trade_CS, data = Til_regressioner_4)
summary(model.2.8h)
model.3.8h <- lm(Avg_return_hyp4 ~ High_ESG_CS + High_trade_CS + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.8h)
model.1.8l <- lm(Avg_return_hyp4 ~ Low_ESG_CS, data = Til_regressioner_4)
summary(model.1.8l)
model.2.8l <- lm(Avg_return_hyp4 ~ Low_ESG_CS + Low_trade_CS, data = Til_regressioner_4)
summary(model.2.8l)
model.3.8l <- lm(Avg_return_hyp4 ~ Low_ESG_CS + Low_trade_CS + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.8l)
model.1.8hml <- lm(Avg_return_hyp4 ~ hml_ESG_CS, data = Til_regressioner_4)
summary(model.1.8hml)
model.2.8hml <- lm(Avg_return_hyp4 ~ hml_ESG_CS + hml_trade_CS, data = Til_regressioner_4)
summary(model.2.8hml)
model.3.8hml <- lm(Avg_return_hyp4 ~ hml_ESG_CS + hml_trade_CS + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.8hml)
```

```r
#Testing high versus low for energy
model.1.9h <- lm(Avg_return_hyp4 ~ High_ESG_nrg, data = Til_regressioner_4)
summary(model.1.9h)
model.2.9h <- lm(Avg_return_hyp4 ~ High_ESG_nrg + High_trade_nrg, data = Til_regressioner_4)
summary(model.2.9h)
model.3.9h <- lm(Avg_return_hyp4 ~ High_ESG_nrg + High_trade_nrg + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.9h)
model.1.9l <- lm(Avg_return_hyp4 ~ Low_ESG_nrg, data = Til_regressioner_4)
summary(model.1.9l)
model.2.9l <- lm(Avg_return_hyp4 ~ Low_ESG_nrg + Low_trade_nrg, data = Til_regressioner_4)
summary(model.2.9l)
model.3.9l <- lm(Avg_return_hyp4 ~ Low_ESG_nrg + Low_trade_nrg + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.9l)
model.1.9hml <- lm(Avg_return_hyp4 ~ hml_ESG_nrg, data = Til_regressioner_4)
summary(model.1.9hml)
model.2.9hml <- lm(Avg_return_hyp4 ~ hml_ESG_nrg + hml_trade_nrg, data = Til_regressioner_4)
summary(model.2.9hml)
model.3.9hml <- lm(Avg_return_hyp4 ~ hml_ESG_nrg + hml_trade_nrg + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.9hml)
```

```
#Testing high versus low for financials
model.1.10h <- lm(Avg_return_hyp4 ~ High_ESG_fin, data = Til_regressioner_4)
summary(model.1.10h)
model.2.10h <- lm(Avg_return_hyp4 ~ High_ESG_fin + High_trade_fin, data = Til_regressioner_4)
summary(model.2.10h)
model.3.10h <- lm(Avg_return_hyp4 ~ High_ESG_fin + High_trade_fin + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.10h)
model.1.10l <- lm(Avg_return_hyp4 ~ Low_ESG_fin, data = Til_regressioner_4)
summary(model.1.10l)
model.2.10l <- lm(Avg_return_hyp4 ~ Low_ESG_fin + Low_trade_fin, data = Til_regressioner_4)
summary(model.2.10l)
model.3.10l <- lm(Avg_return_hyp4 ~ Low_ESG_fin + Low_trade_fin + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.10l)
model.1.10hml <- lm(Avg_return_hyp4 ~ hml_ESG_fin, data = Til_regressioner_4)
summary(model.1.10hml)
model.2.10hml <- lm(Avg_return_hyp4 ~ hml_ESG_fin + hml_trade_fin, data = Til_regressioner_4)
summary(model.2.10hml)
model.3.10hml <- lm(Avg_return_hyp4 ~ hml_ESG_fin + hml_trade_fin + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.10hml)

#Testing high versus low for health care
model.1.11h <- lm(Avg_return_hyp4 ~ High_ESG_HC, data = Til_regressioner_4)
summary(model.1.11h)
model.2.11h <- lm(Avg_return_hyp4 ~ High_ESG_HC + High_trade_HC, data = Til_regressioner_4)
summary(model.2.11h)
model.3.11h <- lm(Avg_return_hyp4 ~ High_ESG_HC + High_trade_HC + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.11h)
model.1.11l <- lm(Avg_return_hyp4 ~ Low_ESG_HC, data = Til_regressioner_4)
summary(model.1.11l)
model.2.11l <- lm(Avg_return_hyp4 ~ Low_ESG_HC + Low_trade_HC, data = Til_regressioner_4)
summary(model.2.11l)
model.3.11l <- lm(Avg_return_hyp4 ~ Low_ESG_HC + Low_trade_HC + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.11l0)
model.1.11hml <- lm(Avg_return_hyp4 ~ hml_ESG_HC, data = Til_regressioner_4)
summary(model.1.11hml0)
model.2.11hml <- lm(Avg_return_hyp4 ~ hml_ESG_HC + hml_trade_HC, data = Til_regressioner_4)
summary(model.2.11hml)
model.3.11hml <- lm(Avg_return_hyp4 ~ hml_ESG_HC + hml_trade_HC + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.11hml)
```

```
#Testing high versus low for industrials
model.1.12h <- lm(Avg_return_hyp4 ~ High_ESG_ind, data = Til_regressioner_4)
summary(model.1.12h)
model.2.12h <- lm(Avg_return_hyp4 ~ High_ESG_ind + High_trade_ind, data = Til_regressioner_4)
summary(model.2.12h)
model.3.12h <- lm(Avg_return_hyp4 ~ High_ESG_ind + High_trade_ind + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.12h)
model.1.12l <- lm(Avg_return_hyp4 ~ Low_ESG_ind, data = Til_regressioner_4)
summary(model.1.12l)
model.2.12l <- lm(Avg_return_hyp4 ~ Low_ESG_ind + Low_trade_ind, data = Til_regressioner_4)
summary(model.2.12l)
model.3.12l <- lm(Avg_return_hyp4 ~ Low_ESG_ind + Low_trade_ind + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.12l)
model.1.12hml <- lm(Avg_return_hyp4 ~ hml_ESG_ind, data = Til_regressioner_4)
summary(model.1.12hml)
model.2.12hml <- lm(Avg_return_hyp4 ~ hml_ESG_ind + hml_trade_ind, data = Til_regressioner_4)
summary(model.2.12hml)
model.3.12hml <- lm(Avg_return_hyp4 ~ hml_ESG_ind + hml_trade_ind + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.12hml)
```

```
#Testing high versus low for materials
model.1.13h <- lm(Avg_return_hyp4 ~ High_ESG_mat, data = Til_regressioner_4)
summary(model.1.13h)
model.2.13h <- lm(Avg_return_hyp4 ~ High_ESG_mat + High_trade_mat, data = Til_regressioner_4)
summary(model.2.13h)
model.3.13h <- lm(Avg_return_hyp4 ~ High_ESG_mat + High_trade_mat + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.13h)
model.1.13l <- lm(Avg_return_hyp4 ~ Low_ESG_mat, data = Til_regressioner_4)
summary(model.1.13l)
model.2.13l <- lm(Avg_return_hyp4 ~ Low_ESG_mat + Low_trade_mat, data = Til_regressioner_4)
summary(model.2.13l)
model.3.13l <- lm(Avg_return_hyp4 ~ Low_ESG_mat + Low_trade_mat + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.13l)
model.1.13hml <- lm(Avg_return_hyp4 ~ hml_ESG_mat, data = Til_regressioner_4)
summary(model.1.13hml)
model.2.13hml <- lm(Avg_return_hyp4 ~ hml_ESG_mat + hml_trade_mat, data = Til_regressioner_4)
summary(model.2.13hml)
model.3.13hml <- lm(Avg_return_hyp4 ~ hml_ESG_mat + hml_trade_mat + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.13hml)

#Testing high versus low for technology
model.1.14h <- lm(Avg_return_hyp4 ~ High_ESG_tech, data = Til_regressioner_4)
summary(model.1.14h)
model.2.14h <- lm(Avg_return_hyp4 ~ High_ESG_tech + High_trade_tech, data = Til_regressioner_4)
summary(model.2.14h)
model.3.14h <- lm(Avg_return_hyp4 ~ High_ESG_tech + High_trade_tech + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.14h)
model.1.14l <- lm(Avg_return_hyp4 ~ Low_ESG_tech, data = Til_regressioner_4)
summary(model.1.14l)
model.2.14l <- lm(Avg_return_hyp4 ~ Low_ESG_tech + Low_trade_tech, data = Til_regressioner_4)
summary(model.2.14l)
model.3.14l <- lm(Avg_return_hyp4 ~ Low_ESG_tech + Low_trade_tech + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.14l)
model.1.14hml <- lm(Avg_return_hyp4 ~ hml_ESG_tech, data = Til_regressioner_4)
summary(model.1.14hml)
model.2.14hml <- lm(Avg_return_hyp4 ~ hml_ESG_tech + hml_trade_tech, data = Til_regressioner_4)
summary(model.2.14hml)
model.3.14hml <- lm(Avg_return_hyp4 ~ hml_ESG_tech + hml_trade_tech + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.14hml)

#Testing high versus low for utilities
model.1.15h <- lm(Avg_return_hyp4 ~ High_ESG_uti, data = Til_regressioner_4)
summary(model.1.15h)
model.2.15h <- lm(Avg_return_hyp4 ~ High_ESG_uti + High_trade_uti, data = Til_regressioner_4)
summary(model.2.15h)
model.3.15h <- lm(Avg_return_hyp4 ~ High_ESG_uti + High_trade_uti + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.15h)
model.1.15l <- lm(Avg_return_hyp4 ~ Low_ESG_uti, data = Til_regressioner_4)
summary(model.1.15l)
model.2.15l <- lm(Avg_return_hyp4 ~ Low_ESG_uti + Low_trade_uti, data = Til_regressioner_4)
summary(model.2.15l)
model.3.15l <- lm(Avg_return_hyp4 ~ Low_ESG_uti + Low_trade_uti + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.15l0)
model.1.15hml <- lm(Avg_return_hyp4 ~ hml_ESG_uti, data = Til_regressioner_4)
summary(model.1.15hml)
model.2.15hml <- lm(Avg_return_hyp4 ~ hml_ESG_uti + hml_trade_uti, data = Til_regressioner_4)
summary(model.2.15hml)
model.3.15hml <- lm(Avg_return_hyp4 ~ hml_ESG_uti + hml_trade_uti + PM2.5_2L_hyp4, data = Til_regressioner_4)
summary(model.3.15hml)
```