The influence of the carbon intensity of investment portfolios on their return and volatility

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Preface

This master thesis is the outcome of a six-month project conducted for Caceis Bank in Amsterdam. This research is executed to graduate from the Master of Financial Engineering and Management at the University of Twente. The six-month period at Caceis Bank has been a great experience thanks to all the people that supported and helped me with this project. First, I want to thank all the employees at the risk solutions department of Caceis for sharing their knowledge and insights. I would like to give special thanks to Marc Maathuis from Caceis for guiding me through the entire project and sharing his expertise. Besides, I want to thank Hans van Erp for his assistance during this project. Moreover, I would like to thank Berend Roorda and Wouter van Heeswijk for the feedback, which helped to greatly improve the quality of this research. Finally, I would like to thank all my friends and family for their support during my study at the University of Twente. The past five years at the University of Twente created life memories.

Benjamin Groeneveld, 2021

Abstract

In society, people have become more and more aware of the climate crisis. This awareness is also present in the financial sector since information on this topic is requested. At Caceis Bank clients such as pension funds cope with the increasing importance of Environmental, Social and Governance related information of their investment portfolios. This demand for information creates the need for research into the topic of the impact that decisions based on environmental considerations have on investment portfolios. One of the main challenges in the realm of sustainability for institutional investors like pension funds is to combine the moral objective of a climate-neutral society with the financial objective of an investment portfolio with an optimal return and risk profile. This research is conducted to extend current literature and to provide practical knowledge to managers and clients of Caceis on the topic of responsible investing. The main research question is: *Do investment portfolios with a low carbon intensity show higher risk-adjusted returns than portfolios with a higher carbon intensity?*

This research employs one asset class, which are the stocks within the Morgan Stanley Capital International World Index over the period 2016-2020. Over this research period, the stocks are scored on their carbon intensity. In each year, three different investment portfolios are created which are a benchmark, a best-in-class portfolio and a worst-in-class portfolio based on carbon intensity. The chosen benchmark portfolio is the MSCI World Index in which approximately 1500-1600 stocks are incorporated. The best-in-class portfolio is constructed from the top twenty per cent performing stocks based on the carbon intensity of each of the eleven sectors within the benchmark portfolio. The worst-in-class portfolio is constructed from the bottom twenty per cent performing stocks based on the carbon intensity of each of the eleven sectors within the benchmark portfolio.

Hence, each year a benchmark, best-in-class and worst-in-class portfolio is constructed. Several performance and risk measures are executed on these portfolios. The most salient measures in this research are return, volatility, Sharpe ratio, Sortino ratio, Treynor ratio and carbon intensity. The results show that from 2017 to 2020 the best-in-class portfolios have the highest historical return and Sharpe ratio for each year. The higher Sharpe ratio indicates that the best-in-class portfolios demonstrate a better historical risk-adjusted return than the benchmark and worst-in-class portfolios.

Besides, normality tests are performed to test whether non-parametric or parametric significance tests fit the daily portfolio returns, weekly volatilities and the results of all measures measured monthly. Applied statistical tests show that for the period 2016 to 2020 the null hypotheses of the benchmark, best-in-class and the worst-in-class distributions of the return, volatility, risk-adjusted measures and the carbon intensity being the same are retained except for the carbon intensity.

Given the above, the results over the research period 2017 to 2020 display that the best-in-class portfolio reveals both better historical returns and historical risk-adjusted returns than the benchmark and worst-in-class portfolio. Namely, over the period 2017 to 2020, the best-in-class portfolio showed an average return of 15.77% yearly in contrast to the benchmark and worst-in-class portfolio which had

an average return of 13.34% and 9.60% respectively. Thereby, the average yearly Sharpe ratio from 2017 to 2020 for the best-in-class portfolio was 1.49 compared to the benchmark and worst-in-class portfolio displaying a Sharpe ratio of 1.22 and 1.07 respectively. Although historically the best-in-class portfolios show better returns and risk-adjusted returns for the years 2017 to 2020, the differences between the three investment portfolios were not found to be statistically significant except for their carbon intensity.

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Acronyms

BIC	Best-in-class
CAPM	Capital asset pricing model
CO2	Carbon dioxide
DVFA	Society of investment professionals in Germany
EMH	Efficient-market hypothesis
ESG	Environmental, Social, Governance
ETF	Exchange-traded funds
ETS	Emission trading scheme
EU	European Union
EUA	European Union emission allowance
GHG	Greenhouse gas emissions
ISIN	International securities identification number
KPI	Key performance indicator
MPT	Modern portfolio theory
MSCI	Morgan Stanley Capital International
PA	Paris agreement
PMPT	Post-modern portfolio theory
PPM	Parts per million
SRI	Socially responsible investing
VAR	Value at Risk
WIC	Worst-in-class
WICI	World intellectual capital initiative

1 Introduction

In this chapter, an introduction into the company and the faced problem by the company is presented. Subsequently, the objective of this research is defined together with the research scope. Afterwards, the research questions to solve the stated core problem are provided. Moreover, a methodology is specified to systematically obtain the knowledge needed for conducting this research. Finally, the outline of this research is given which states in which chapter the research questions are answered.

1.1 Introduction to the company

Caceis is a French banking group. The Dutch branch of Caceis operates as a branch of the French Caceis Banking group. Caceis is a European market leader in the field of asset servicing and fund administration. The Dutch branch of Caceis is located in Amsterdam and merged with Kas Bank. Caceis is dedicated to serving asset managers, fund managers, banks and brokers, private equity, and real estate funds. Offices are spread over Europe, North and South America, and Asia. Caceis delivers several services such as execution, clearing, forex, security lending, custody, depositary, fund administration, fund distribution support, middle office outsourcing, and issuer services.

This master thesis will be conducted for the risk solutions department of Caceis. The risk solutions department executes calculations for clients on the Value at Risk, Expected Shortfall, volatility, Probability of Default, forex risk, spreads, and Environmental, Social, and Governance aspects. In addition to monitoring risk, the risk solutions department performs simulations and stress tests. Finally, reports according to the need of clients are set up covering the aspects of the performance and risk profile of the investment portfolios.

1.2 Research motivation

The risk solutions department at Caceis recently started to receive more and more Environmental, Social, and Governance (ESG) investing-related questions from clients. The clients of Caceis cope with the increasing importance of ESG related aspects in their investment portfolios. The objective of carbon neutrality drives demand for information about the environmental pillar of ESG investing and its influence on investment portfolios. Several questions concerning the impact of ESG investing are not yet answered. This request for information on the topic of ESG investing creates a demand for an investigation into the influence, significance, and impact of ESG investing on investment portfolios.

1.3 Problem description

In order to understand the causes leading to the core problem faced, a problem cluster is presented in Figure 1. A problem cluster maps the causal relationships between problems. Next to providing causal relationships, a problem cluster lays out a visual representation of the problems. The problem cluster assists to determine the core problem Caceis faces. From the presented problem cluster the core problem can be derived. Heerkens and van Winden (2017) state that the core problem to be chosen should be influenceable. The scope of this research is on the impacts of ESG investing on the risk and returns of investment portfolios. The influence of ESG investing on the risk and returns are the main interest of the clients of Caceis and limiting them down to these topics makes the master thesis assignment feasible within the time constraint.

The problem cluster in Figure 1 displays the core problem at the top of the diagram. To solve the problem of making adequate management decisions on the topic of ESG investing concerning investment portfolios, several other problems must be solved. In addition, the problems of estimating the impact of ESG investing on both the risk and returns of investment portfolios arise.

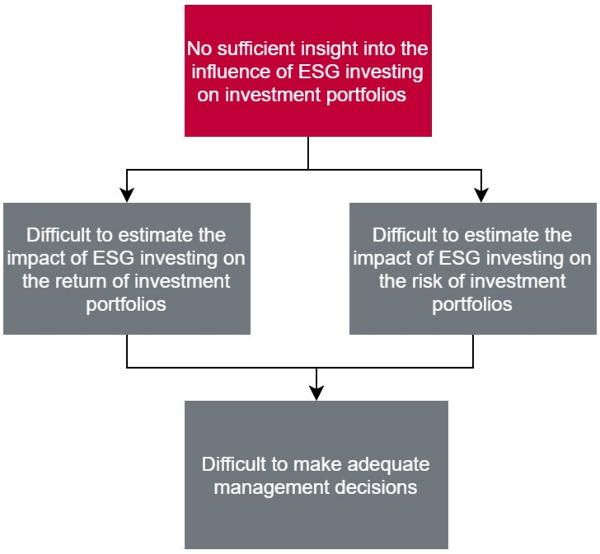


Figure 1: Problem cluster

All the previously mentioned problems are causes of the core problem: *"The management of Caceis does not have sufficient insight into the influence of ESG investing on investment portfolios in order to support pension funds in making adequate management decisions."*

1.4 Research objective

A challenge for institutional investors is to combine the moral objective of contributing to a climate-neutral society with the financial objective of an investment portfolio with an optimal return and risk profile. This thesis investigates to what extent these objectives can be reached simultaneously. The insights should create a foundation for management decisions regarding ESG investing within investment portfolios. The insights on this topic are obtained from literature on ESG investing and the construction of investment portfolios. Analysis on the investment portfolios is performed to acquire knowledge based on the difference between the portfolios. Along these lines, Caceis can inform clients more in-depth on the topic of ESG investing regarding their investment portfolios.

1.5 Research scope

The time available for the master thesis is limited, therefore defining a scope is of importance. The scope of the research is determined by the core problem. The previously mentioned core problem is: *"The management of Caceis does not have sufficient insight into the influence of ESG investing on investment portfolios in order to support pension funds in making adequate management decisions."* To solve this action problem, there is a need of solving several knowledge problems. There is a need for a broader insight into the topic of ESG investing, therefore research questions must be set up to create a foundation to answer the core problem. The goal of this research is to identify the impact and influence of ESG investing on investment portfolios. There is a need of combining several subjects such as ESG investing, returns and risk management. Knowledge on each topic must be acquired, and finally these topics must be combined.

Furthermore, this research focuses on investment portfolios concerning their carbon emissions. Carbon emission is one of the main topics that is concerned with the Environmental pillar of ESG investing. The focus on the carbon intensity of investment portfolios stems from the fact that insight into this specific topic would yield the highest amount of reward relative to other subjects, since most questions of clients arise around this topic. To evaluate carbon-based investment portfolios several models are examined. Ultimately, the focus of this research is on the impact of the carbon intensity of investment portfolios on their return and volatility.

1.6 Research questions

In this section, sub-research questions are given which help to answer the main research question. These research questions also assist to obtain the knowledge needed to finally solve the core problem. The ideal result of this master thesis is to provide Caceis and its clients with knowledge on the topic of different investment portfolios with high and low carbon intensity to see the disparity in their risk and returns. Therefore, the main research question to be answered is: *Do investment portfolios with a low carbon intensity show higher risk-adjusted returns than portfolios with a higher carbon intensity?*

To answer the main research question four sub-research questions are formulated to be able to answer the main research question. The first sub-question aims to identify the subject and concepts of ESG investing. After the concepts of ESG investing are researched, the second sub-question can be investigated which raises the question of how investment portfolios can be constructed. The construction of the carbon-intensity-based investment portfolios creates the basis on which several models can be tested. In this way, the impact of carbon emissions on the return and risk of investment portfolios can be tested. Therefore, the two up following sub-questions seek to quantify the return, risk and significance associated with the different investment portfolios. The last sub-question tries to answer how the obtained empirical findings can be translated into decision support for managers. The associated sub-questions are given as follows:

1a. What are the concepts of ESG investing?

1b. What is the relation between ESG investing, stock returns and risk according to literature?

1c. What is the history of carbon awareness?

1d. What is the relation between carbon emission, stock returns and risk according to literature?

2. How can the carbon-intensity-based investment portfolios be constructed?

3a. How can the return, volatility and risk-adjusted returns of high and low carbon-intensity investment portfolios be determined according to historical data?

3b. How can the statistical significance of the different investment portfolios be tested?

4. How can the empirical findings be translated into decision support?

1.7 Methodology

In this section, the methodology is presented to solve the research problems, which provides the knowledge that must be obtained to solve the core problem. This methodology systematically provides the procedures to identify the needed information for this research.

1. Literature study

Literature research is performed to answer the research questions regarding the topic of ESG investing and its influence on investment portfolios. The first part of the literature study focuses on the three main concepts of responsible investing. Furthermore, more in-depth literature research on one of the main concepts of responsible investing is conducted. Besides, the relation of carbon emission with risk and return is reviewed. Finally, literature on developing a suiting analysis for this research is provided to measure the impact that carbon emissions have on investment portfolios.

2. Data collection

The knowledge to be acquired mainly comes from scientific literature. Next to scientific literature, a company called "Sustainalytics" provides historical data on the carbon emissions of listed companies. In this study, investment portfolios are constructed based on the carbon intensity from the database of Sustainalytics. The stock allocation of the MSCI World Index is extracted from SimCorp Dimension to construct investment portfolios based on their carbon intensity. Finally, the adjusted close price data of stocks are obtained from the Yahoo Finance database.

3. Data analysis

When the data has been obtained, it can be analysed and processed. First, the data must be analysed to confirm it does not have erroneous form and employable content. Second, it is required to clean and prepare the data for the analysis. Finally, the analysis consists of calculations that show the return, volatility, risk-adjusted return and risk measures of the different constructed investment portfolios.

4. Result analyses

To answer the main research questions, the results and outcome of the analysis must be assessed. The significance of the daily stock return data, weekly volatility data, and the yearly and monthly performance metrics are tested with hypothesis testing. Finally, a conclusion and discussion are derived from the results and analysis.

1.8 Outline

The literature in Chapter 2 and Chapter 3 provides all information on the theories and analyses used in this master thesis. Thereby, the literature study answers research questions 1, 2 and 3. Furthermore, Chapter 4 describes the data collection and the characteristics of the data used for this research. Chapter 5 describes the method of how the three different investment portfolios based on carbon intensity are constructed. Chapter 6 presents the results from the analysis of the investment portfolios. Finally, Chapter 7 gives a discussion and conclusion which will answer research question 4 and the main research question. Moreover, Chapter 7 provides limitations and recommendations for future research.

2 Literature study

In this chapter, a literature review on the main concepts of responsible investing is given. Additionally, a review on ESG investing and its effect on risk and returns according to the literature will be examined. Moreover, literature about carbon emissions concerning risk and return is provided. Besides, literature on the awareness of carbon emission and carbon emission allowances is given.

2.1 Main concepts of responsible investing

In this section, responsible investing is described as the overarching concept in which several other areas of responsible investing are included. With responsible investing, investors incorporate the effect that their investments have on people and the planet in their strategy. Along these lines, investments are not only based on financial decisions. Schueth (2003) defines responsible investing as the process of integrating personal values and societal concerns into investment decision-making. He also discusses that the origin of responsible investing dates back hundreds of years ago, where the Jewish law supervised investing responsibly. Large amounts of money invested according to responsible investing principles reported in 2010 by the Social Investment Forum and the Eurosif reflect the increasing importance of responsible investing (Von Wallis & Klein, 2015).

Several factors play a role in implementing responsible investing. Liang and Renneboog (2017) conclude that socially responsible practices are a result of the legal regime in a country. Next to legal practices, Hong and Kostovetsky (2012) show that political groups can have an effect on corporate social responsibility and this group invests accordingly which could make the cost of capital in these socially responsible firms lower. Due to globalisation and socio-political trends, the societal demand for embedding social responsibility into the finance sector increases (Puaschunder, 2016).

Hill (2020) describes three main principles for responsible investing. These three concepts are ESG investing, socially responsible investing (SRI), and impact investing. All these categories have different views on responsible investing. In sections 2.1.1, 2.1.2 and 2.1.3 an elaboration on the three different concepts of responsible investing is presented. Finally, an explanation of the focus on one of the three concepts that will be used throughout this master thesis is given.

2.1.1 ESG investing

Van Duuren, Plantinga, and Scholtens (2016) describe that ESG factors focus on non-financial dimensions of stock performance. The dimensions of ESG are environmental, social, and governance. ESG investors gather stock information about all these three dimensions and analyse it. This analysis forms an overview of the sustainability of a company. Generally, funds have minimal standards regarding ESG scores. ESG investing beliefs that investors and society both benefit from including ESG information in investment decisions (Van Duuren et al., 2016).

2.1.2 SRI

Statman (2006) describes responsible investing as the integration of personal values and societal concerns with investment decisions. Renneboog, Ter Horst, and Zhang (2008) define socially responsible investments as a process that integrates social, environmental and ethical considerations into the decision-making process. The Social Investment Forum distinguishes three main SRI strategies which are screening, shareholder advocacy, and community investing (Berry & Junkus, 2013). Investors that include SRI take the effect of investments on people and the planet into account. In this way, investors try to align their personal values with their investment strategies. Usually, the main purpose of investing is to generate a return. Nilsson (2008) states that if a consumer has a poor view on the return of investments it would hurt the incentive to invest. The reverse may also be true, when good performance on SRI is expected people tend to invest in these investments often without caring about the SRI aspects. An SRI-driven investor tries to minimise the impacts on both people and the planet, therefore it is less likely that such an investor would invest in Tobacco, Gambling, and Alcohol. In conclusion, the focus of SRI is mainly on the impact of investments and to reallocate scarce resources towards socially responsible investments.

2.1.3 Impact investing

The term impact investing was first used by a discussion of investors in 2007 (Bugg-Levine & Emerson, 2011). Impact investing combines philanthropy and financial investment. Clarkin and Cangioni (2016) define impact investing as investments that are primarily made to create tangible social impact but also have the potential for financial return. Impact investing has two focal points which are generating positive returns and social and environmental aspects. While impact investors are still profit-seeking, the negative impact on social and environmental aspects should be limited. Bugg-Levine and Emerson (2011) state that the idea behind impact investing is that investors can still pursue financial returns while also addressing social and environmental challenges. Investors employing impact investing are willing to give up some return if necessary, to reduce the impact on social and environmental issues. Impact investors show that businesses not necessarily are all evil, but businesses can also be used for good purposes.

2.1.4 Relation of ESG, SRI and impact investing

A characteristic that sets ESG apart from SRI and impacting investing is that ESG mainly focuses on the long-term. ESG investing enhances long-term value with the help of identifying risks and growth opportunities. ESG not only focuses on responsible investing but also on creating long-term value. On the other hand, in socially responsible investing and impact investing less attention is paid to financial outcomes and the mitigation of risks, and the identification of growth opportunities. Figure 2 displays that ESG investing is placed between conventional financial investing and impact investing, in terms of social and environmental returns according to Hill (2020) that created the figure with empirical evidence. ESG investing tries to encompass both responsible investing as taking into consideration risks and growth opportunities.

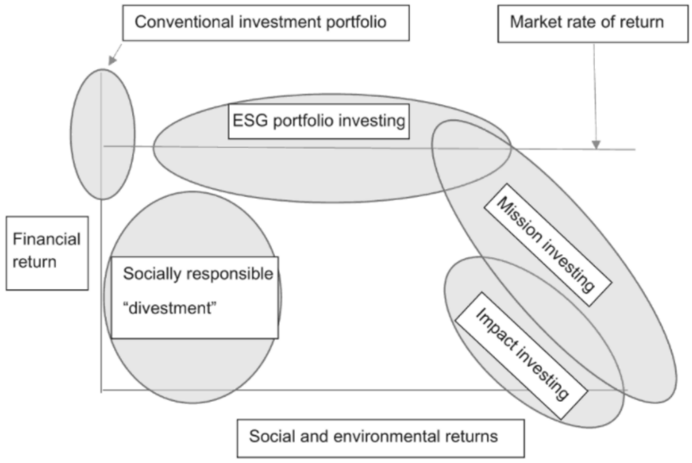


Figure 2: Financial return versus social and environmental returns (Hill, 2020)

2.2 ESG Investing

Investment funds try to both incorporate ESG factors and the objective to reduce volatility and optimise returns within their investment portfolios. This master thesis focuses on a specific part of ESG investing which is carbon emission, instead of the other concepts. In 2004 the process to share thoughts and perspectives on Environmental, Social, and Governance (ESG) investing was launched. In June 2004 over 20 financial institutions published a paper with the title "Who cares Wins: connecting financial markets to a changing world". The paper of Compact (2004) states that a better involvement of ESG factors in the decisions of investments would result in more stable and predictable markets. The terms Environmental, Social and Governance also have been discussed at a conference called "Who cares Wins" convened in Zurich in August 2005. Asset managers, institutional investors, government bodies, and regulators came together to examine the role of ESG investing in the financial markets. The above events created the first milestones in the establishment of ESG investing.

2.2.1 ESG metrics

A framework of key performance indicators (KPIs) on ESG factors is developed with the help of the World Intellectual Capital Initiative (WICI). The goal of the initiatives by the WICI is to develop a generally accepted framework on intangibles (Bassen & Kovacs, 2008). The German society of investment professionals (DVFA) created a new standard for ESG reporting. According to Bassen and Kovacs (2008), this standard aims to generate a consistent and comprehensive framework for ESG reporting for analyses of the performance of corporations. For each of the three aspects of ESG investing general KPIs were set up which are presented in Table 1.

Table 1: DVFA Key Performance Indicators (Bassen & Kovacs, 2008)

	Environmental	Social	Governance
General KPIs For all industry groups	Energy efficiency	Staff Turnover	Contributions to Political Parties
	Deployment of Renewable energy sources	Training & Qualification	Anti-competitive Behaviour, Monopoly
		Maturity of Workforce	Corruption
		Absenteeism	
		Restructuring-related Relocation of Jobs	

Giese et al. (2017) also provide a framework on the three pillars of ESG with 10 themes and 37 key ESG issues. Figure 3 provides an overview of the methodology by Morgan Stanley Capital International (MSCI).

3 Pillars	10 Themes	37 ESG Key Issues	
Environment	Climate Change	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	Natural Resources	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building	Opp's in Renewable Energy
Social	Human Capital	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	Product Liability	Product Safety & Quality Chemical Safety Financial Product Safety	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing	
	Social Opportunities	Access to Communications Access to Finance	Access to Health Care Opp's in Nutrition & Health
Governance	Corporate Governance	Board Pay	Ownership Accounting
	Corporate Behavior	Business Ethics Anti-Competitive Practices Tax Transparency	Corruption & Instability Financial System Instability

Figure 3: Research methodology overview (Giese, Lee, Melas, Nagy, & Nishikawa, 2017)

Both the frameworks mentioned by Bassen and Kovacs (2008) and Giese et al. (2017) provide insight into the focus of ESG investing metrics. A further extension of this literature review will provide insights into how with the help of metrics an ESG rating of a company can be obtained.

2.2.2 ESG integration

There are several ways to incorporate ESG investing into an investment portfolio. Sahut and Pasquini-Descomps (2015) describe three main types which are negative screening, positive screening and active investment. Amel-Zadeh and Serafeim (2018) state that negative screening is the most frequently used approach. Negative screening means that companies exclude sin stocks and firms that do not comply with international norms and standards. Negative screening methods are often norm-based. The stocks of companies that are involved in the production of tobacco, alcohol, and gaming are called sin stocks (Salaber, 2007). By excluding firms that produce harmful products for people or the environment, investors incorporate their values into their investment strategy. On the other hand, a more rare screening method by investors is called positive screening (Amel-Zadeh & Serafeim, 2018). Positive screens often pick shares that have superior standards in terms of corporate social responsibility standards (Renneboog et al., 2008). An example of a positive screening method is best-in-class ESG factor integration which favours companies with a better rate on ESG criteria within the same sector (Sahut & Pasquini-Descomps, 2015). By only including the top performers of a group, investors limit down their overall investments to a certain percentage of the total group. Van Duuren et al. (2016) define active investing as an investment strategy that pursues to beat the benchmark index on a risk-adjusted basis. Using active investment as a strategy for implementing ESG investing should not only yield positive risk-adjusted returns but is also positive for the entire globe.

2.2.3 ESG ratings

There are several companies providing information on ESG investing. Three of the largest companies providing information on ESG ratings are Sustainalytics, MSCI and Thomson Reuters. ESG ratings are scored differently by the companies. MSCI is considered to be the largest data provider, and Sustainalytics forms the basis of fund-level ESG ratings (Christensen, Serafeim, & Sikochi, 2019). ESG ratings measure how well a firm is managing ESG risks and opportunities (Serafeim & Yoon, 2021). There has been a discussion on the disparity of ESG ratings by firms. The ESG rating providers described above have different scales and often lack consistency. These problems may be derived from the fact that ESG information could be highly subjective and is often estimated by the information providers.

Gibson, Krueger, and Schmidt (2019) used the ESG rating of six different ESG information providers of a sample of S&P 500 firms from 2013 to 2017 and found that the correlation between the ESG ratings was about 0.46. Another interesting finding of Gibson et al. (2019) was that the average correlation was the lowest for the governance pillar and the highest for the environmental pillar ratings.

2.2.4 ESG and returns

Premiums next to the risk-free rate can arise due to rewards for bearing risk, behavioural biases and market impediments (Cornell, 2021). Malkiel and Fama (1970) describe the efficient-market hypothesis (EMH), which is a hypothesis that states that in an efficient market, prices fully reflect available information. Under this hypothesis, when ESG information arrives in the financial markets the market should adapt to this ESG information to reach the market equilibrium again.

Verheyden, Eccles, and Feiner (2016) state that ESG information can present itself as an extra set of intelligence to provide insight into future performance. Taking the pillars of ESG into consideration with investment decisions means that there is a focus on long-term value creation rather than short-term benefits.

There have been several studies claiming that high-rated sustainability firms outperform the low-rated ones. Eccles, Ioannou, and Serafeim (2014) researched 180 U.S. companies over 18 years and found that the high sustainability firms outperformed the low sustainability firms for both the stock market and accounting measures. Eccles et al. (2014) describe a high sustainability firm as one with a higher level of stakeholder engagement, a longer-term time horizon matched with long-term investors, greater attention to non-financial measures, a greater emphasis on external and social standards, measurement of the performance of suppliers, and a high level of transparency of non-financial information. Kempf and Osthoff (2007), and Statman and Glushkov (2009) evaluated a trading strategy in which high social responsible investment rated stocks were bought and low rated stocks were sold of the S&P 500 over the years 1992-2004, the result being that abnormal returns could be obtained by adopting this strategy. Abnormal returns can be described as the difference between actual return and the competitive return which is the return just enough to maintain a capital investment (Jacobsen, 1988).

On the contrary, several studies state that high sustainability firms do not necessarily outperform the low rates ones. The study of Halbritter and Dorfleitner (2015) found that ESG portfolios do not show significant differences in returns using high and low rated ESG levels, both for the individual pillars of ESG and its overall score. The difference between Halbritter and Dorfleitner (2015), and the study of Eccles et al. (2014) and Kempf and Osthoff (2007) could stem from the fact that both the latter two studies only used one ESG dataset and due to their specific period of investigation. Mănescu (2011) provides more insight into the topic of individual ESG dimensions, the study found that only one aspect of ESG which was community relations had a positive effect on stock returns. The study of Mănescu (2011) on the other hand states that firms might reduce their cost of capital by promoting ESG concerns.

To summarise, there have been several studies showing different results of the relationship between ESG investing and stock returns. The differences may stem from the type of analysis, the focus of the metrics or the period researched.

2.2.5 ESG and risk

Ross, Westerfield, and Jaffe (2002) describe two types of risk namely systematic and unsystematic risk. Systematic risk is any risk that affects a large number of assets, each to a greater or lesser agree, and unsystematic risk is a risk that specifically affects a single asset or a small group of assets (Ross et al., 2002).

Verheyden et al. (2016) show that ESG screening reduces the tail risks, which is a chance of loss that occurs given a probability distribution. De and Clayman (2015) found a strong negative relationship between ESG and volatility, and this relationship strength increased when the market volatility increased. Fulton, Kahn, and Sharples (2012) conclude that firms with high ESG scores have lower risk and lower cost of capital.

The findings of Kaiser (2020) are in line with the so-called risk-mitigation hypothesis, which means that firms with a high sustainability rating often generate lower returns but have benefits concerning risk. Respondents on a survey executed by Amel-Zadeh and Serafeim (2018) believe that incorporating ESG information into investment decisions is also relevant for reputational, legal and regulatory risk.

2.3 Carbon emission

Carbon emission is part of the environmental pillar of ESG investing and this metric is the focus of this research. In this section, a more in-depth overview of the relation between carbon emissions and financial systems is described. Besides, the history and the development concerning carbon emissions are described. Finally, relationships between carbon emission and stock return, and carbon emission and volatility in the literature are reviewed.

2.3.1 History of carbon emission awareness

Greenhouse gas emissions (GHG), and in particular carbon dioxide (CO2) is considered to be one of the main causes of global warming (Soytas, Sari, & Ewing, 2007). As the global atmospheric concentration of CO2 was 280 parts per million (ppm) in 1750 according to Soytas et al. (2007), it is expected that the concentration will reach 550 ppm by 2050 (Wang, Luo, Zhong, & Borgna, 2011). This increase in the value of CO2 in ppm provides insight into the development of the increase in the CO2 concentration over time.

One of the first catalysts concerning the development of awareness on climate change began in 1972 in Stockholm on which a conference was held (Bodansky, 2001). Several years later in 1987, a report called the “Brundtland Commission report” was published. The report stresses the importance of protecting the environment. A widely used definition of sustainable development was given in this report which is “the development that meets the needs of the present without compromising the ability of the future generations to meet their own needs” (Burton, 1987). At a future point in time, Clark (1989) describes how economic and social aspects are important to achieve sustainable development.

To combat this increase in CO2 emissions, several events were set up. In 1997 the Kyoto protocol was launched. The Kyoto protocol formulates legally binding emission targets for industrialised countries between 2008 and 2012 (Böhringer, 2003). Another legally binding framework was adopted in December 2015 by 196 parties, which is called the Paris agreement. In contrast to the Kyoto Protocol, the Paris agreement does not set up individual targets for the reduction of emissions (Streck, Keenlyside, & Von Unger, 2016). The Paris agreement aims to reach a certain goal and parties can choose to what extent they want to contribute. All participants must come up with an ambitious reduction plan of their CO2 emissions every five years. Bodansky (2016) discusses the legal character of the Paris agreement and concludes that making the agreement legally binding can make the commitment better, but parties may not participate and set less ambitious commitments.

2.3.2 Carbon emission allowances

In January 2005 carbon emission allowances were granted to European firms by the European Union (EU), in which firms that choose to pollute more than their allowances can buy more of these allowances from firms that pollute less than their allowances (Oestreich & Tsiakas, 2015). This cap-and-trade program for CO2 is also known as the EU Emissions Trading Scheme (ETS). Oestreich and Tsiakas (2015) explain that the EU ETS sets an annual cap for the total emission and that the total emission allowances are allocated among the CO2 emitters. Xia, Hao, Qin, Ji, and Yue (2018) mention a benefit of the cap-and-trade system, which is the flexibility of selling their allocated permits that are not used in the carbon trade market. The first future contracts were announced in March 2005 (Narayan & Sharma, 2015). These carbon future contracts are called EU Emission Allowance (EUA) contracts.

2.3.3 Carbon emission and returns

A compelling question is how climate change will affect stock returns. An interesting finding of Veith, Werner, and Zimmermann (2009) is that stock returns of electricity producers are positively correlated with the increase of carbon prices. Furthermore, Oberndorfer (2009) found a positive relationship between the performances of EU Emission Allowance (EUA) and the stock returns of the most important European electricity firms.

On the other hand, Kumar, Managi, and Matsuda (2012) did not found a significant relationship between carbon prices and stock return of firms considered clean energy firms. Bushnell, Chong, and Mansur (2013) conclude that within the power sector the companies with the highest emissions rates performed better than the cleaner firms in terms of share prices. Apparently, the market understood that the cleaner electricity firms declined more in price than the ones with the highest emissions due to the fact that the market revenue effect outweighs the effect of the cost savings from lower CO2 prices (Bushnell et al., 2013). Bolton and Kacperczyk (2020b) found a widespread carbon premium over 14,400 companies in 77 countries, which means higher stock returns for companies with higher carbon emissions.

2.3.4 Carbon emission and risk

The EU ETS market forces companies that are CO2-intensive to include the cost of these EUA in their operative decision and this price of carbon brings risk for stock returns of utility companies (Koch & Bassen, 2013). Oestreich and Tsiakas (2015) suggest that companies with high carbon emissions have a high exposure to carbon risk, which should then display higher expected returns. Also, Bolton and Kacperczyk (2020a) conclude that investors will price in carbon risk.

Monasterolo and De Angelis (2020) researched the impact that the Paris Agreement (PA) has on the stock market. The study states that the level of systematic risk for the low-carbon indices has decreased significantly after the PA, concluding that after the PA the market considers the low-carbon indices as less risky and more attractive for investment.

2.4 Conclusion

Chapter 2 tries to answer the first and second research questions. Research question 1a is: *What are the concepts of ESG investing?* The three dimensions of ESG investing are Environmental, Social and Governance, and ESG investing combines information on these three pillars for the measurement of the sustainability of a company. ESG investing tries to let both society and investors benefit from ESG information.

Research question 1b is: *What is the relation between ESG investing, stock returns and risk according to literature?* The relation between ESG investing and returns can be described as ESG information could be a set of information to provide insight into the future performance of investments. In terms of risk, studies show that ESG investing can reduce tail risk and show a lower cost of capital.

Research question 1c is: *What is the history of carbon awareness?* One of the first events that resulted in a change in the awareness of carbon was a conference in Stockholm in 1972. Several years later reports were published that stressed the importance of protecting the environment. Besides, the Kyoto Protocol and the Paris agreement were formed to reach the objective of reducing carbon emissions.

Research question 1d is: *What is the relation between carbon emission, stock returns and risk according to literature?* Studies showed that the market could see carbon emission as a risk and therefore should show higher expected returns.

Research question 2 is: *How can the carbon-intensity-based investment portfolios be constructed?* The literature describes several methods to include ESG information into an investment portfolio. Three types of integration are called negative screening, positive screening and active investment. Negative screening excludes sin stocks such as firms producing tobacco, alcohol, and games. Positive screening picks stocks with superior standards in terms of social responsibility. The strategy of active investment aims for beating the benchmark on a risk-adjusted basis.

This master thesis employs the positive screening method since the carbon intensity is used to create investment portfolios with superior performance in terms of carbon intensity. All in all, Chapter 2 provides answers to the first and second research questions.

3 Performance analysis concepts

The main research question tries to answer whether the investment portfolio that has a low carbon intensity shows a higher risk-adjusted return than the portfolio that has a high carbon intensity. To answer this main research question, several methods to calculate returns and risk are reviewed in this chapter. All the theories and concepts described in this chapter in combination with the taken assumptions provide a framework to analyse the research topic.

3.1 Introduction to analysis methods

This section presents some historical research on financial frameworks which is interesting to consider throughout the described performance analysis concepts. The history of some concepts that take returns, risk and diversification into account is provided. Besides, the theories and mathematical formulas used in this thesis for obtaining the returns and risks are discussed. Afterwards, concepts of performance measurement such as the Sharpe ratio, Sortino ratio and the Treynor ratio come by to be able to discuss whether the returns obtained are justified by the risk taken within a portfolio. Finally, statistic hypothesis testing models are described to test the significance of the results of the investment portfolios.

Markowitz (1952) first presented a framework for investment portfolios optimising expected returns and minimising the investment risk an investor is willing to take, this framework is called modern portfolio theory (MPT). The model of Markowitz (1952) can be used by investors in order to reach diversification within an investment portfolio. The MPT framework determines the risk of the portfolio with the help of the variance and does not only use the downside risk. In contrast to the MPT, Rom and Ferguson (1994) developed the Post-modern portfolio theory (PMPT), which only takes downside risk into account. So, the MPT and PMPT differ in terms of how the risk of the investment portfolio is determined.

A broadly employed model by investors to estimate returns is called the capital asset pricing model (CAPM) which helps to determine abnormal returns of which the basic model is developed by Treynor (1961), Sharpe (1964), Linter (1965) and Mossin (1966). Sharpe (1966) and Treynor and Black (1973), both came up with ratios to take return and risk into account. Sharpe (1966) and Treynor and Black (1973) use the standard deviation in their ratios. On the other hand, Treynor and Mazuy (1966) and Jensen (1968) used the market risk also known as Beta in their ratios.

3.2 Measurement of historical returns

Bacon (2008) defines the performance of a portfolio as the increase or decrease in the value of the assets given a specific period. Two types of measuring returns are simple returns and logarithmic returns. The simple return of the portfolio is the sum of the weighted simple returns of the individual assets within the portfolio (Panna, 2017). Simple returns are not time additive, on the other hand, logarithmic returns have time additive attributes (Siddikee, 2018). In other words, simple returns aggregate over assets and logarithmic returns aggregate over time. Due to the multiple stocks within the different investment portfolios in this thesis, simple returns are better applicable to the adjusted close prices on both a daily and yearly basis.

Simple returns are used because the individual weight of the assets within the MSCI World Index that is used as a benchmark in this research can be multiplied with its daily return and accordingly all these individual asset returns can be added to get the daily return of the whole. The daily returns of a portfolio can be used for calculating the volatility of the portfolio. For the calculation of the daily returns the first trading day P_{t-1} and the next trading day P_t are input for equation (1). In order to calculate the return of a whole year, equation (1) is used with the input of P_{t-1} being the adjusted close price of the first trading day of the year and P_t being the adjusted close price of the last trading day of the year. The yearly return of a portfolio is calculated by taking the sum of the weighted simple yearly returns of the individual assets within the portfolio. The simple return is calculated by

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

The portfolio return R_p is calculated with the associated weight w_i of asset i and the simple return of asset R_i. The portfolio return is given by

$$R_p = \sum w_i * R_i \tag{2}$$

3.3 Measurement of historical volatility

The volatility of a variable can be defined as the standard deviation of the returns over a given time period (Hull, 2012). The daily standard deviation of the portfolio is calculated by taking the sample standard deviation of all the daily returns of a portfolio within a year. The daily standard deviation of a portfolio is calculated by

$$\hat{\sigma}_p = \sqrt{\frac{\sum\left(R_p - \overline{R_p}\right)^2}{N-1}} \tag{3}$$

In equation (3) R_p represent the individual daily portfolio return of the sample and $\overline{R_p}$ is the mean daily portfolio return over the total period. The letter N is the total number of daily returns in the sample. The annualised volatility is calculated by

$$\hat{\sigma}_{p(annualy)} = \sigma_{p(daily)} * \sqrt{T} \tag{4}$$

In equation (4), $\hat{\sigma}_{p(annualy)}$ is the annual estimated volatility of a portfolio, $\sigma_{p(daily)}$ is the daily volatility and T is the number of trading days in a year which is assumed to be 252 in this research.

3.4 Measurement of risk-adjusted returns

The total return on its own is an incomplete measure of the performance of a portfolio since it ignores risk (Modigliani & Leah, 1997). The CAPM model described in section 3.1 shows that investors want to get higher expected payoffs with greater risk, which is also described as the risk premium. To assess the performance on a risk-adjusted basis, three measures are used in this thesis which are the Sharpe ratio, the Sortino ratio and the Treynor ratio.

All of the mentioned ratios need the risk free rate R_f as an input, therefore a risk-free rate must be determined. Damodaran (1999) mentions two restrictions for choosing a risk-free rate, which is that it should have no default risk and no reinvestment risk. Houweling and Vorst (2002) confirm that credit default swap markets use the swap rate as their risk-free rate. Hull, Predescu, and White (2004) conclude that the risk-free rate that is used by market participants is about 10 basis points less than the 5-year swap rate on average. Also, Blanco, Brennan, and Marsh (2004) use the swap rate as their risk-free rate and find that the credit default swap spread is quite close to the bond yield spreads.

In this thesis, portfolios over the years 2016 to 2020 are researched. Over all these years the same risk-free rate is used, which is chosen according to the findings of Hull et al. (2004). Since this research starts with data from 01-04-2016, the chosen five-year swap rate (USD) at 01-04-2016 was 1.67%, and minus the 10 basis points the chosen risk-free rate is set to 1.57%. In conclusion, for all the research years 2016 to 2020, 1.57% is chosen to be de risk-free rate. In this way, the two restrictions mentioned by Damodaran (1999) of the risk-free rating having no default risk and no reinvestment risk are approached due to keeping a fixed risk-free rate over the research period of five years.

The Sharpe ratio was first introduced by Sharpe (1966), the paper presented a measurement for the performance of mutual funds that both considers return and risk. The Sharpe ratio is also known as the reward-to-variability ratio (Sharpe, 1994). The Sharpe ratio shows the reward per unit of variability (Sharpe, 1966). When using the Sharpe ratio the stock returns must be approximately normally distributed to not get deceptive results. Officer (1972) concluded from empirical findings that the stock returns did not all have the stable properties of a normal distribution since the tails were considered to be fatter. Aparicio and Estrada (2001) found that stock returns had fatter tails, higher peaks and that the skewness had a different direction than a normal distribution. The Sharpe ratio is a function of the return of the portfolio R_p, the risk-free rate R_f and the standard deviation σ_p of the daily portfolio returns. The Sharpe ratio is given as follows

$$Sharpe\ ratio\ = \frac{R_p - R_f}{\sigma_p} \tag{5}$$

When ranking the Sharpe ratios of different portfolios, it must be interpreted as the higher the outcome of the ratio the more desirable in cases of portfolios with positive excess returns (McLEOD & van Vuuren, 2004).

The Sortino ratio was proposed by Sortino and Price (1994). The Sortino ratio uses downside deviation instead of the standard deviation (Rollinger & Hoffman, 2013). In (6), $\sigma_{p-negative}$ represents the standard deviation of the negative daily returns. A higher Sortino ratio is considered to earning more per unit of “bad risk” that it takes. Mohan, Singh, and Ongsakul (2016) describe that upside volatility which is used in the Sharpe ratio is a bonus for investment, and therefore should not be considered risky. The R_p and the R_f represent the return of the portfolio and the risk-free rate respectively. The Sortino ratio is given by

$$Sortino\ ratio \ = \frac{R_p - R_f}{\sigma_{p-negative}} \tag{6}$$

In addition to the other two risk-adjusted measures, the Treynor ratio is considered. The Treynor ratio compares the portfolio risk premium to the systematic risk with the help of the beta (Verma & Hirpara, 2016). Hence, the Treynor ratio specifies the return per unit of risk beta β_p in contrast to the Sharpe ratio that uses the portfolio standard deviation σ_p (Scholz & Wilkens, 2005). The calculated betas are considered to be ex-post. The Beta β_{p-BIC} is calculated by the covariance of the daily returns of the best-in-class (BIC) portfolio R_{p-BIC}, the daily returns of the benchmark portfolio $R_{p-Benchmark}$ and the variance of the benchmark portfolio daily returns $Var(R_{p-Benchmark})$. The beta for the BIC portfolio is calculated by

$$\beta_{p-BIC} = \frac{Cov(R_{p-BIC}, R_{p-Benchmark})}{Var(R_{p-Benchmark})} \tag{7}$$

The Beta β_{p-WIC} is calculated by the covariance of the daily returns of the worst-in-class (WIC) portfolio R_{p-WIC}, the daily returns of the benchmark portfolio $R_{p-Benchmark}$ and the variance of the benchmark portfolio daily returns $Var(R_{p-Benchmark})$. The beta for the WIC portfolio is calculated by

$$\beta_{p-WIC} = \frac{Cov(R_{p-WIC}, R_{p-Benchmark})}{Var(R_{p-Benchmark})} \tag{8}$$

The Treynor ratio is calculated by the daily returns of the portfolio R_p, the risk-free rate R_f and the Beta of the portfolio β_p. The Treynor ratio is given by

$$Treynor\ ratio\ = \frac{R_p - R_f}{\beta_p} \tag{9}$$

The interpretation of the Treynor is rather similar to the Sharpe ratio. When excess returns of a portfolio are positive, a higher ratio is preferred. This means that for each unit of market risk a higher return was obtained.

The risk of the associated portfolio over a year is calculated with the Value at Risk (VaR). Hull (2012) describes VaR as a measure that tells with a certainty percentage X not more than an amount of money V is lost in T days. The variable V represents the VaR of the portfolio, and it is a function of the variables X and T, where T is the total number of trading days in a year. The historical daily Value at Risk VaR_{daily} is calculated with the 5 percentile return since a confidence level of 5% is employed. It depends on the total number of days T of the whole year, of which the lowest observation given the 5% confidence level is chosen. When for example $T = 252$, the 5-percentile return is the 12th lowest observation when rounded down. For a more in-depth explanation of the historical VaR calculation in a non-parametric setting see Cheung and Powell (2012). The yearly VaR is calculated by

$$Annual\ VaR\ = VaR_{daily}\ * \sqrt{T} \tag{10}$$

In this section, the origin and characteristics of several measures were provided. The returns of the portfolios are calculated with simple returns. The volatility is calculated with the estimated sample standard deviation. Furthermore, the risk-adjusted returns are calculated with the Sharpe ratio, the Sortino ratio and the Treynor ratio. Finally, the Value at Risk is given which represents that the portfolio would not lose more than a certain value given a confidence level and the period of one year.

3.5 Carbon intensity

In this master thesis, investment portfolios are constructed according to their carbon intensity values. The performances of the different portfolios based on carbon intensity are examined in this research. Hoffmann and Busch (2008) define carbon intensity as a ratio of the carbon usage to a related business metric. Zhou, Zhang, Song, and Wang (2019) define carbon intensity as the ratio of carbon emissions to economic output. Literature shows characteristics concerning carbon intensity and firms. For example, Gazheli, Van Den Bergh, and Antal (2016) found that sectors with high carbon intensity show an absolute growth in both their output and emissions, which means that it can be difficult for so-called dirty sectors to grow greener. Richter and Schiersch (2017) researched exporting firms and non-exporting firms in Germany, their results showed that exporting firms can generate more sales for the same amount of CO2 emissions than that non-exporting firms in the same defined sector. Furthermore, this raises the questions whether globalisation and free trade is beneficial for the environment.

Kumar and Firoz (2018) calculate the carbon intensity by the yearly total emissions divided by the yearly total revenue of a company. In equation (11) the total CO2 emissions are measured in tons and the input revenues are given in millions of dollars. With the help of the carbon intensity, the firms can be compared for different firm sizes across the eleven sectors used in this research. On the other hand, Cole, Elliott, Okubo, and Zhou (2013) researched Japanese firms and found a strong effect of firm size, which means that large firms emit fewer emissions per unit of output than smaller firms presumably due to economies of scale in resources or abatement. Nevertheless, the carbon intensity is the best alternative that can be used in this thesis since this measure was able to be calculated with the provided data of Sustainalytics. The total CO2 emissions in equation (11) are the sum of Scope 1 and Scope 2 emissions. Scope 3 emissions were not included in the delivered database. The yearly carbon intensity of a firm is given by

$$Carbon\ intensity\ = \frac{total\ CO2\ emissions}{total\ revenue} \tag{11}$$

In total three portfolios are constructed each year which are a benchmark, a best-in-class and a worst-in-class portfolio based on their carbon intensity. The benchmark portfolio is used to assess the overall performance of the other two portfolios. The best-in-class portfolio represents the top twenty per cent of stocks from the benchmark portfolio and the worst-in-class portfolio represents the worst twenty per cent of the benchmark portfolio in terms of their carbon intensity. A more in-depth explanation of the investment portfolio construction is provided in Chapter 5.

3.6 Statistical hypothesis testing

In this section, the normality tests that will be performed on the results are explained. Besides, the characteristics of the distributions of the benchmark, BIC and WIC portfolios are given. Moreover, the assumptions on the data and the chosen hypothesis tests that are performed on the results of the benchmark, BIC and WIC investment portfolios are provided.

3.6.1 Normality tests

In order to test the normality of the distributions of the benchmark, BIC and WIC investment portfolios normality tests are performed. Hypothesis tests will be performed on the daily stock returns, weekly volatility and the six measures measured yearly and monthly. These six measures are return, volatility, Sharpe ratio, Sortino ratio, Treynor ratio and carbon intensity. Two types of testing are used to test the distributions for normality. First, for the daily stock returns, weekly volatility and the six measures, the normality is tested with the help of the Shapiro-Wilk and Kolmogorov tests with a confidence level of 0.05. In addition, the skewness and kurtosis z-values are calculated to determine whether these are similar to the skewness and kurtosis of a normal distribution with a confidence level of 0.05. The skewness and kurtosis provide information on the symmetry and tail information respectively. The z-values of the skewness are determined by:

$$Skewness\ z - value = \frac{Skewness\ statistic}{Skewness\ standard\ error} \tag{12}$$

The z-values of the kurtosis are determined by:

$$Kurtosis\ z - value = \frac{Kurtosis\ statistic}{Kurtosis\ standard\ error} \tag{13}$$

The z-values of the skewness and kurtosis with a confidence level of 0.05 must be within the boundaries of -1.96 and 1.96 to assume normality. Table 2 displays the two types of tests for normality employed, which are normality tests and the information on the symmetry and tails of the distributions.

Table 2: Normality tests

Normality test	Symmetry and tail information
Shapiro-Wilk	Skewness (symmetry)
Kolmogorov-Smirnov	Kurtosis (tail)

3.6.2 Characteristics of the data

To determine an appropriate hypothesis test to the results of the benchmark, BIC and WIC portfolios, the characteristics of the data must be determined. Besides, assumptions on the characterises of the data must be made. First, a number of three categorical groups are tested for differences, namely the benchmark, BIC and WIC portfolios. Second, the distributions of the three groups are assumed to be independent and identically distributed. Third, the data is considered to be continuous since it can take any value.

3.6.3 Statistical hypothesis testing

The research of Nandy (2014) shows similarities with this master thesis research. Nandy (2014) compared the returns of an index exchange-traded fund (ETF) and matched index mutual funds. The study used the Kruskal-Wallis hypotheses tests and assumed that the returns of the two groups are independent. In this master thesis also different bundles of stocks which can be considered to be ETFs, are researched. Nandy (2014) mentioned that another study by Sharifzadeh and Hojat (2012) did also quantitatively compare index ETFs and matched index mutual funds. Sharifzadeh and Hojat (2012) measured the difference of the Sharpe ratios of the investment portfolios with the Wilcoxon signed-rank nonparametric hypothesis test, which assumes that the Sharpe ratios are dependent. Nandy (2014) on the other hand states that the Sharpe ratios of the index ETFs and the matched index mutual funds must be assumed to be independent and describes that this is a flaw of the study of Sharifzadeh and Hojat (2012).

In this master thesis, the nonparametric Kruskal-Wallis test to compare the benchmark, BIC and WIC portfolios is performed when the data is assumed to be not normally distributed. By using this nonparametric test, the benchmark, BIC and WIC portfolios are assumed to be independent. An advantage for this research is that the Kruskal Wallis test does not assume underlying distributions of the returns, volatility, Sharpe ratio, Sortino ratio, Treynor ratio and carbon intensity. The Kruskal-Wallis test compares the medians of the benchmark, BIC and WIC portfolios. The Kruskal-Wallis tests do not need a normal distribution of the samples, but it is required that the benchmark, BIC and WIC show rather similar distributions. Besides, a complementing parametric test of the Kruskal-Wallis test is the one-way ANOVA test. This test is used for the data that is assumed to be normally distributed. Although an ANOVA test can be considered to be quite robust with a sufficiently large sample size when the data is not assumed to be normally distributed, it is chosen to apply the One-way ANOVA on assumed parametric distributions and the Kruskal-Wallis Test when the distributions of the data are considered to be non-parametric. Table 3 provides an overview of the parametric and non-parametric tests that will be used on the results.

Table 3: Types of tests used for testing differences

Parametric	**Non-parametric**
One-way ANOVA	Kruskal-Wallis Test

3.7 Conclusion

Chapter 3 tries to answer research questions 3. Research question 3a is: *How can the return, volatility and risk-adjusted returns of high and low carbon-intensity investment portfolios be determined according to historical data?* To determine the historical returns of the investment portfolios, simple returns are used. The volatility is calculated with the sample standard deviation of the daily stock returns of the investment portfolios. Besides, the risk-adjusted returns are calculated with the Sharpe ratio, Sortino ratio and the Treynor ratio. Moreover, the one-year Value at Risk is calculated to provide insights into the historical risk of the investment portfolios. Lastly, the carbon intensity of the investment portfolios is calculated with the total CO_2 emission and revenue of the companies. Research question 3b is: *How can the statistical significance of the different investment portfolios be tested?* The results of the measures are tested for normality with the skewness, kurtosis, Shapiro-Wilk test and Kolmogorov-Smirnov test to determine whether a parametric or non-parametric test applies to the results. The parametric test used is the one-way ANOVA and the complementing non-parametric test employed is the Kruskal-Wallis test.

4 Data collection

In this chapter, the data collection method is given. Besides, the selection of the databases is described. Moreover, the structure, origin and content of the databases are explained.

4.1 Database selection

The first selected database is an ESG dataset of the data provider Sustainalytics. More specifically, a carbon emission dataset that is a component of the ESG database of Sustainalytics is used. Sustainalytics is a Morningstar company and is a leading firm in providing ratings and analytics that support investors to invest responsibly. Sustainalytics already had a co-operation with Caceis, therefore the ESG database employed in this thesis is delivered by Sustainalytics. The scope of this research is on the carbon intensity of investment portfolios. Therefore, the database of Sustainalytics focusing on carbon emissions that contains data of listed companies all over the world is used.

The second dataset employed is the data of the allocation of the stocks within the MSCI World Index. For every year from 2016 to 2020, the stock allocation of the MSCI World index is used to construct carbon intensity-based investment portfolios. The MSCI World index contains approximately 1650 stocks a year from around thirty countries all over the world. The allocation of the stocks in each year is obtained from a program called SimCorp Dimension, which is an investment management software solution used by Caceis.

The third dataset used is the adjusted close price data from the Yahoo Finance database. The adjusted close price of a stock is the close price adjusted for corporate actions such as stock splits and the effect of dividends on the stock price. For all the stocks within the MSCI World Index, the daily adjusted closes prices were extracted for the period 2016 to 2020. Through the utility of the programming language Python, this data was obtained.

To summarise, three datasets have been obtained for this research which are carbon emission data of Sustainalytics, the stock allocation data of the MSCI World Index extracted with SimCorp Dimension and the adjusted close price data of the stocks within the MSCI World Index obtained from the Yahoo Finance database.

4.2 Database structure and content

All the datasets described in section 4.1 have different characteristics and contain different data of which the combination is needed in this research. In this section, the structure and content of each dataset are explained.

The carbon emissions in the dataset provided by Sustainalytics are divided into three groups which are Scope 1 emissions, Scope 2 emissions and total emissions. The total emissions are the sum of Scope 1 and Scope 2 emissions. Sinha, Schew, Sawant, Kolwaite, and Strode (2010) state that Scope 1 emission includes direct emission sources from within an organisation and Scope 2 emission includes indirect emission sources from outside the organisation. The dataset also contains the yearly revenue in millions of dollars of the listed companies, and the carbon intensity is also provided. The carbon intensity is calculated by dividing the total carbon emissions in tons by the total revenue of the company in millions of dollars. The data of Sustainalytics on the carbon emissions of the listed companies can be estimated or reported. This means that data on carbon emissions can be reported by the company itself in for example an annual report or it can be an estimated value by Sustainalytics.

The MSCI World Index has been assigned as the benchmark portfolio since its stock allocation is ubiquitous. The benchmark portfolio is used to compare different portfolios based on carbon intensity. Table 4 displays the number of stocks and countries within the MSCI World index over the years 2016 to 2020.

Table 4: Total number of stocks and countries within MSCI World index

Year	**# of stocks**	**# of countries**
2016	1652	30
2017	1654	30
2018	1653	30
2019	1633	29
2020	1646	28

The countries within the MSCI World index stem from five regions all over the world. Table 5 presents the regions and the designated countries to a certain region.

Table 5: Countries represented in the MSCI World Index

Africa / Middle East	**Asia / Pacific**	**Europe**	**Latin America and Caribbean**	**United States and Canada**
Israel	Australia	Austria	Argentina	Canada
South Africa	China	Belgium	Bermuda	United States
	Hong Kong	Channel Islands	Mexico	
	Japan	Denmark		
	Macau	Finland		
	New Zealand	France		
	Papua New Guinea	Germany		
	Singapore	Ireland		
		Italy		
		Luxembourg		
		Netherlands		
		Norway		
		Portugal		
		Spain		
		Sweden		
		Switzerland		
		United Kingdom		

The methodology behind the MSCI World index is described as comprehensive and consistent. Since it is constructed both globally, across several regions, all market capitalisation sizes and several sectors and segments it is a suitable index to use in this research.

Besides the dataset of Sustainalytics and the MSCI World index allocation, the daily adjusted close prices of the stocks within the MSCI World index are required. The adjusted close prices of the companies that are included in the sample are obtained from the Yahoo Finance database. Since a large set of daily close prices must be gathered, a code extracting all data was used with the help of the programming language Python. Afterwards, the daily stock returns could be calculated with the daily adjusted close price over the required time horizon.

4.3 Conclusion

In total three datasets have been employed in this research. First, the dataset of Sustainalytics on the carbon emissions of listed companies was selected. This data on carbon emission was divided by Scope 1, Scope 2 and total emissions. Second, the data of the MSCI World index allocation was obtained. For the research period of 2016 to 2020, there were around 1650 stocks within the MSCI World index each year. These 1650 stocks came from five different regions all over the world. Third, the daily adjusted close price data of the stocks within the MSCI World index were extracted from Yahoo Finance. Finally, these three datasets can be used for the construction of investment portfolios.

5 Portfolio construction

Chapter 5 elucidates the construction of three different investment portfolios. Moreover, the process of combining the datasets and the screening method on which the portfolios are based are presented. Besides, the conversion of the different currencies present in the investment portfolio is explained.

5.1 Screening method

The literature review in Chapter 2 defines several strategies on how a portfolio could be constructed. For this research, the BIC and WIC method is chosen. The BIC stocks represent the stocks that show the lowest carbon intensity. The BIC method is a positive screening method since it chooses the superior performing stocks from the sample. The WIC stocks are considered to be the stocks with the highest carbon intensity. For the BIC and WIC portfolios, the top and bottom twenty per cent performers of each sector are chosen respectively. The stocks can fall within one of the eleven sector types available.

To make the benchmark, BIC and WIC portfolios as identical as possible except for their carbon intensity, the same weights as within the MSCI World Index allocation are assigned to each stock. Also, the weights of the sector of the benchmark, BIC and WIC portfolio is constructed such that they are identical. Table 6 provides an example of the sector types and the complementing weights within each type of investment portfolio.

Table 6: Illustration on the weight per sector within the investment portfolios

Sector	Weight in benchmark, BIC and WIC
Consumer Discretionary	13.12%
Consumer Staples	9.98%
Energy	5.72%
Financials	18.14%
Healthcare	13.58%
Industrials	11.12%
Information Technology	14.63%
Materials	3.70%
Real Estate	3.10%
Telecommunications	3.54%
Utilities	3.35%
Total	100%

In conclusion, the BIC and WIC portfolios are constructed with the best and worst-performing stocks concerning carbon intensity respectively. The portfolios are constructed based on carbon intensity since the carbon intensity takes the size factor of the companies into account in comparison to using carbon emissions that do not consider the size of the companies.

5.2 Data filtering process

The time horizon of the data is 2016 to 2020. This time horizon is chosen for the reason of the data of Sustainalytics and the MSCI World Index matching the best in order to minimise blank data. First, the data of the allocation of the MSCI World Index was taken. Within this dataset, several International Securities Identification Numbers (ISIN) were not available. The stocks of which the ISIN were not available, have been removed from the sample since the ISIN number is needed to connect all datasets. Second, the data of the stock allocation was matched with the carbon emission data of Sustainalytics. After this match, some data of certain stocks were not available within the dataset of Sustainalytics and therefore these blanks were removed. Third, adjusted close prices of the stocks were matched with the other two datasets. After this match, there were multiple stocks of which the adjusted close price data was not (totally) available within the Yahoo Finance database. In conclusion, three datasets have been connected and during this process, some data has been removed. Table 7 displays the remained amount of data during the cleaning and preparation process of each step.

Table 7: Amount of data during the preparation process

Year	# of stocks within MSCI World Index	# of stocks left after removing blanks within MSCI World Index allocation	# of stocks left after matching data of Sustainalytics	# of stocks left after matching price data
2016	1652	1622	1466	1326
2017	1654	1645	1528	1383
2018	1653	1647	1566	1440
2019	1633	1629	1567	1466
2020	1646	1646	1610	1520

An important step within the connection of the datasets is the match between the adjusted close price data and the data of the carbon emission. For each year from 2016 to 2020, three portfolios are examined. The investment strategy is based on carbon intensity, which means that each year the most recent available carbon emission data was used and screened. The data on carbon emission is yearly data, which means that for each listed company a yearly number is available. The extraction date is the date on which Sustainalytics extracted the data on carbon emissions.

The reported carbon emission data is collected by Sustainalytics by annual reports. Logically, at least a year must be completed to be able to form an annual report. Afterwards, the annual reports must be formed and published by the companies and this process often takes some months. In the end, Sustainalytics can collect and process this carbon emission data. This process of obtaining the most recent data by Sustainalytics makes that the decision on carbon intensity data is based on another year than on which the return data is calculated. In other words, the strategies of the three different investment portfolios employ the most recent available carbon emission data. Table 8 displays the match of the carbon emission data and the stock returns.

Table 8: Match of return and carbon emission data

Year of return data	Year of carbon emission data	Extraction date by Sustainalytics
2016	2014	3-1-2016
2017	2015	3-1-2017
2018	2016	9-1-2018
2019	2017	3-1-2019
2020	2018	1-1-2020

5.3 Currency conversion

Approximately 30 countries are represented within the MSCI World Index each year. These countries often have different currencies. In total, a set of fourteen different currencies can be found within the portfolios over the period 2016 to 2020. Table 9 presents the currencies within the investment portfolios.

Table 9: Currency types and abbreviations

Currency	Currency abbreviations
Australian Dollar	AUD
Canadian Dollar	CAD
Swiss Franc	CHF
Danish Krone	DKK
Euro	EUR
British Pound	GBP
Hong Kong Dollar	HKD
Israeli new shekel	ILS
Japanese Yen	JPY
Norwegian Krone	NOK
New Zealand dollar	NZD
Swedish Krona	SEK
Singapore dollar	SGD
United States dollar	USD

The currency conversion of all stocks took several steps. First, all the daily stock returns were calculated for each year of the stock's original currency. Second, all the daily exchange rates for each type of currency within the investment portfolios to the currency USD were obtained. Third, all the daily stock returns were converted to USD. The currency USD has been chosen because the carbon intensity of the firms is calculated by Sustainalytics with the revenue of companies in millions of USD.

5.4 Conclusion

The dataset of the MSCI World Index allocation, Sustainalytics and the daily adjusted close price data have been connected to fit the need of this thesis. The top and bottom performers based on carbon intensity are presented in the BIC and WIC portfolios respectively. During the creation of these BIC and WIC portfolios for the period 2016 to 2020, data has been removed and filtered. Furthermore, an explanation on the match of the return data and carbon emission data was provided. Finally, the process of the conversion of all the different currencies within the investment portfolios is described and explained.

6 Results and analysis

In this chapter, the results of the applied theories and models presented in Chapters 2 and Chapter 3 are given. More specifically, this chapter provides an outcome of the analysis of the constructed portfolios of which the objective is to obtain insight into the effect of carbon intensity on investment portfolios.

6.1 Benchmark portfolios 2016-2020

In this section, the outcome of the analysis of the benchmark portfolios of the year 2016 to 2020 is provided. Some general numbers on the benchmark portfolios are given and thereby information on the performance and carbon intensity is presented.

The first analysis was performed on the benchmark portfolios of 2016 to 2020. In consecutive order, the general numbers of the portfolios consist of the total number of stocks within the portfolio, the total number of countries represented in the portfolio, the total number of sectors and the number of reported and estimated numbers concerning the carbon intensity. Table 10 provides an overview of general information over the total research period.

Table 10: Information on total numbers of benchmark portfolios 2016-2020

Year	Total # stocks	Total # countries	Total # sectors	Total reported	Total estimated
2016	1326	30	11	755	571
2017	1383	30	11	808	575
2018	1440	30	11	943	497
2019	1466	29	11	846	620
2020	1520	28	11	916	604

The total number of stocks within the benchmark portfolio ranges from 1326 in 2016, to 1520 in 2020. Each subsequent year the number of data increases. These stocks stem from approximately 30 countries and they are divided into 11 sectors. The average amount of stocks of which the information is reported of the benchmark portfolios is 59.76% over the whole research period. Table 11 provides the performance data of the benchmark portfolios of 2016 to 2020.

Table 11: Performance data of benchmark portfolios 2016-2020

Year	Return	Annualised volatility	Sharpe	Sortino	Treynor	Carbon intensity
2016	10.92%	13.732%	0.681	0.836	0.094	155.634
2017	22.15%	5.586%	3.684	5.937	0.206	192.59
2018	-11.16%	12.585%	-1.011	-1.276	-0.127	188.618
2019	26.48%	10.565%	2.357	2.932	0.249	173.079
2020	15.90%	34.858%	0.411	0.506	0.143	176.252

From 2016 to 2020 the return of the benchmark portfolios ranged from -11.16% to 22.15% and the annualised volatility was the lowest in 2017 and the highest in 2020. The Sharpe, Sortino and Treynor ratios were negative in 2018 due to negative returns but were positive for all the other researched years. The total carbon intensity of the benchmark portfolios showed an average of 177.235 over the years 2016 to 2020.

Table 12 shows the historical Value at Risk values which is the maximum expected amount to be lost within the designated year with a confidence level of 95.0%. If the portfolio would be worth one million dollars at the beginning of the year, then Table 12 shows the values that the portfolios will not lose more than the presented Value at Risk values.

Table 12: One-year historical Value at Risk of the benchmark portfolios of 2016-2020

Year	Value at Risk ($)	Value at Risk (%)
2016	$194,806	19.48%
2017	$78,463	7.85%
2018	$248,681	24.87%
2019	$169,319	16.93%
2020	$460,998	46.10%

6.2 Best-in-class portfolios 2016-2020

In this section, the results of the best-in-class portfolios from 2016 to 2020 are presented. The general information on the best-in-class portfolio is provided. Also, the performance data and Value at Risk outcomes are given.

First, the general information of the best-in-class portfolio is provided. The total number of stocks within the best-in-class portfolios are the top twenty per cent performing stocks based on the carbon intensity of the benchmark portfolios of each sector. The number of stocks ranges from 266 to 303 stocks in 2016 and 2020 respectively. The total number of countries that are represented within the best-in-class portfolios decreased to a level of approximately 23 in comparison to approximately 30 countries in the benchmark portfolios. The total number of reported values on carbon emission of companies increased from an average of the benchmark of 59.76% per cent to an average of the best-in-class of 78.52% per cent. Table 13 shows all the values on the general numbers of the best-in-class portfolios.

Table 13: Information on total numbers of best-in-class portfolios 2016-2020

Year	Total # stocks	Total # countries	Total # sectors	Total reported	Total estimated
2016	266	22	11	198	68
2017	276	23	11	211	65
2018	288	24	11	249	39
2019	294	23	11	243	51
2020	303	23	11	220	83

Second, Table 14 displays the performance data of the best-in-class portfolios over the period 2016 to 2020. The returns over the years range from -10.76% in 2018 to 32.14% in 2019. The annualised volatility is the lowest in 2017 and the highest in 2020. The risk-adjusted returns are negative for 2018 and positive for the other researched years. The carbon intensity of the BIC portfolios showed an average of 25.568 in contrast to the benchmark portfolios that showed an average of 177.235 over the period from 2016 to 2020.

Table 14: Performance data of best-in-class portfolios 2016-2020

Year	Return	Annualised volatility	Sharpe	Sortino	Treynor	Carbon intensity
2016	6.21%	14.579%	0.318	0.375	0.047	26.012
2017	23.67%	5.841%	3.783	6.357	0.222	30.159
2018	-10.76%	12.910%	-0.955	-1.203	-0.123	27.791
2019	32.14%	11.645%	2.626	3.448	0.285	25.574
2020	18.02%	33.412%	0.492	0.536	0.199	18.304

Third, Table 15 provides the one-year Value at Risk for the BIC portfolios for all research years. The Value at Risk values of the BIC portfolios is presented with a confidence level of 95.0% and a portfolio value of $1,000,000 at the beginning of each year.

Table 15: One-year historical Value at Risk of the best-in-class portfolios of 2016-2020

Year	Value at Risk ($)	Value at Risk (%)
2016	$197,986	19.80%
2017	$86,097	8.61%
2018	$246,651	24.67%
2019	$156,328	15.63%
2020	$435,061	43.51%

6.3 Worst-in-class portfolios 2016-2020

In this section, the results of the WIC portfolios over the period 2016 to 2020 are provided. The general information, the performance data and the values of the Value at risk per year are given in this section.

First, the information on the total numbers is provided. The total number of stocks within the WIC portfolios are the same as the BIC portfolios each year since the WIC portfolios select the top worst twenty per cent performing stocks based on carbon intensity from each sector. The total number of countries represented within the WIC portfolios ranges from 19 to 26. The average of the reported carbon emission values by the companies of the WIC portfolios is 53.07%, which is the lowest average of all the three constructed portfolios.

Table 16: Information on the total numbers of the worst-in-class portfolios 2016-2020

Year	Total # Stocks	Total # Countries	Total # Sectors	Total reported	Total estimated
2016	266	19	11	137	129
2017	276	24	11	149	127
2018	288	26	11	158	130
2019	294	26	11	136	158
2020	303	24	11	178	125

Second, Table 17 displays the information on the performance data of the WIC portfolios. The lowest return was obtained in the year 2018 and the highest return was obtained in 2019. The annualised volatility of the WIC portfolios ranges from 6.100% in 2017 to 31.668% in 2020. The risk-adjusted returns were negative in 2018 and showed positive values in the other years. The average of the carbon intensity is 531.651 of the WIC portfolios, which is the highest value of all three portfolios.

Table 17: Performance data of worst-in-class portfolios 2016-2020

Year	Return	Annualised Volatility	Sharpe	Sortino	Treynor	Carbon intensity
2016	13.65%	13.564%	0.891	1.035	0.130	476.512
2017	21.97%	6.100%	3.344	5.398	0.196	555.645
2018	-13.45%	12.501%	-1.201	-1.584	-0.155	555.680
2019	24.74%	11.383%	2.035	2.693	0.223	513.705
2020	5.13%	31.668%	0.113	0.123	0.046	556.714

Third, Table 18 provides the Value at Risk numbers of the WIC portfolios. These numbers provide the maximum expected amount lost over one year with a confidence level of 95.0% and a portfolio value of one million dollars at the beginning of each year.

Table 18: One-year historical Value at Risk of the worst-in-class portfolios of 2016-2020

Year	Value at Risk ($)	Value at Risk (%)
2016	$219,989	22.00%
2017	$98,936	9.89%
2018	$202,746	20.27%
2019	$184,611	18.46%
2020	$513,609	51.36%

All in all, this section provided all the results of the benchmark, BIC and WIC portfolios from 2016 to 2020. The general numbers that characterise the different portfolios are presented. For each year and portfolio type, the historical performances are shown together with the Value at Risk measures.

6.4 Analysis 2016-2020

In this section, a summary of all the portfolio types of the period 2016 to 2020 is provided to better show the different performances of the portfolio types. First, yearly calculated numbers are provided on the performance of the portfolios. So, the yearly returns, volatility and risk-adjusted measures are shown. Besides, an insight is provided into what would have happened when the portfolios strategies were adopted at the beginning of 2016 and readjusted every year. Second, insights into the monthly calculated performances are given with the help of graphs and tables. The monthly returns and volatility of the three portfolio types are displayed. Moreover, the Sharpe, Sortino and Treynor ratios over 2016 to 2020 of the BIC and WIC portfolios are plotted into one graph to see what relationship the two datasets have. Besides, a long-short strategy has been made with the monthly return data of the BIC and WIC portfolios.

Table 19 presents an overview of several performance measures for all investment portfolios over the period 2016 to 2020.

Table 19: Summary of all measures from 2016-2020

Year	Portfolio Type	Return	Annualised Volatility	Sharpe	Sortino	Treynor	Beta	Carbon intensity
2016	benchmark	10.92%	13.732%	0.681	0.836	0.094	1.000	155.634
	BIC	6.21%	14.579%	0.318	0.375	0.047	0.989	26.012
	WIC	13.65%	13.564%	0.891	1.035	0.130	0.926	476.512
2017	benchmark	22.15%	5.586%	3.684	5.937	0.206	1.000	192.59
	BIC	23.67%	5.841%	3.783	6.357	0.222	0.997	30.159
	WIC	21.97%	6.100%	3.344	5.398	0.196	1.042	555.645
2018	benchmark	-11.16%	12.585%	-1.011	-1.276	-0.127	1.000	188.618
	BIC	-10.76%	12.910%	-0.955	-1.203	-0.123	1.005	27.791
	WIC	-13.45%	12.501%	-1.201	-1.584	-0.155	0.970	555.680
2019	benchmark	26.48%	10.565%	2.357	2.932	0.249	1.000	173.079
	BIC	32.14%	11.645%	2.626	3.448	0.285	1.073	25.574
	WIC	24.74%	11.383%	2.035	2.693	0.223	1.041	513.705
2020	benchmark	15.90%	34.858%	0.411	0.506	0.143	1.000	176.252
	BIC	18.02%	33.412%	0.492	0.536	0.199	0.825	18.304
	WIC	5.13%	31.668%	0.113	0.123	0.046	0.775	556.714

The year 2016 was the first year researched. In this year the WIC portfolio showed the highest historical return of 13.65%. On the contrary, for the years 2017 to 2020, the BIC portfolios showed the highest returns. In order to compare these different performances of returns, the risk-adjusted measures should be considered. Considering the returns of the investment portfolios by itself does not take into account the amount of risk that was taken. Therefore three ratios that take risk into account were employed. The interpretation of the risk-adjusted returns is more difficult than the results of the returns alone. When the returns on themselves are considered, the higher the return the more desirable. On the other hand, when risk-adjusted returns are compared it must be noted that the interpretation of negative risk-adjusted returns is more subjective. Positive risk-adjusted returns can be assessed as the higher the outcome the more desirable. So, for all the researched years except for 2018, the results can be interpreted as the higher the risk-adjusted returns the more desirable it is. In 2018 the three investment portfolios showed both negative returns and risk-adjusted returns. A negative risk-adjusted return could mean that the risk-free rate is greater than the return of the portfolio or that the return of the portfolio is negative. McLEOD and van Vuuren (2004) provides two examples of negative Sharpe ratios which are hard to interpret. The two examples show that when negative Sharpe ratios are considered, the least negative Sharpe ratio is not necessarily the highest return for the unit of risk taken. In 2016 the Sharpe, Sortino and the Treynor ratio were the highest for the WIC portfolio. For the period 2017 to 2020 the Sharpe, Sortino and the Treynor ratio were the highest for the BIC portfolio. But the highest value for the risk-adjusted returns in 2018 must not naïvely be considered as the most desirable.

Table 20: Average numbers per portfolio type from 2016-2020

Year	Portfolio Type	Return	Annualised Volatility	Sharpe	Sortino	Treynor	Carbon intensity
2016-2020	benchmark	12.86%	15.465%	1.224	1.787	0.113	177.235
	BIC	13.86%	15.677%	1.253	1.903	0.126	25.568
	WIC	10.41%	15.043%	1.036	1.533	0.088	531.651

Table 20 provides an overview of the average performance numbers over the period 2016 to 2020 for each portfolio type. The table shows the average numbers for the yearly measures taken from Table 19 to obtain an indication of the results over the whole research period. The average number for the returns is the highest for the BIC portfolio and the lowest for the WIC portfolio. The Sharpe, Sortino and the Treynor ratio also were the highest for the BIC portfolio. Table 20 contains some strong assumptions such as considering the averages and negative risk-adjusted returns. Nevertheless, the average values show that the return and risk-adjusted returns of the BIC are the most desirable in comparison to the other two investment portfolios.

In the following figures and tables, an overview is given of what would have happened if you invested one million dollars into the benchmark, BIC or WIC portfolio at the beginning of 2016. It is important to note that each investment strategy of a portfolio type is restructured every year. So, for the BIC each year the top twenty best-performing stocks per sector on the most recent information of the carbon intensity is incorporated within the strategy. This also accounts for the WIC portfolio, where the most recent information on the worst top twenty per cent stock performances of each sector in terms of carbon intensity is incorporated.

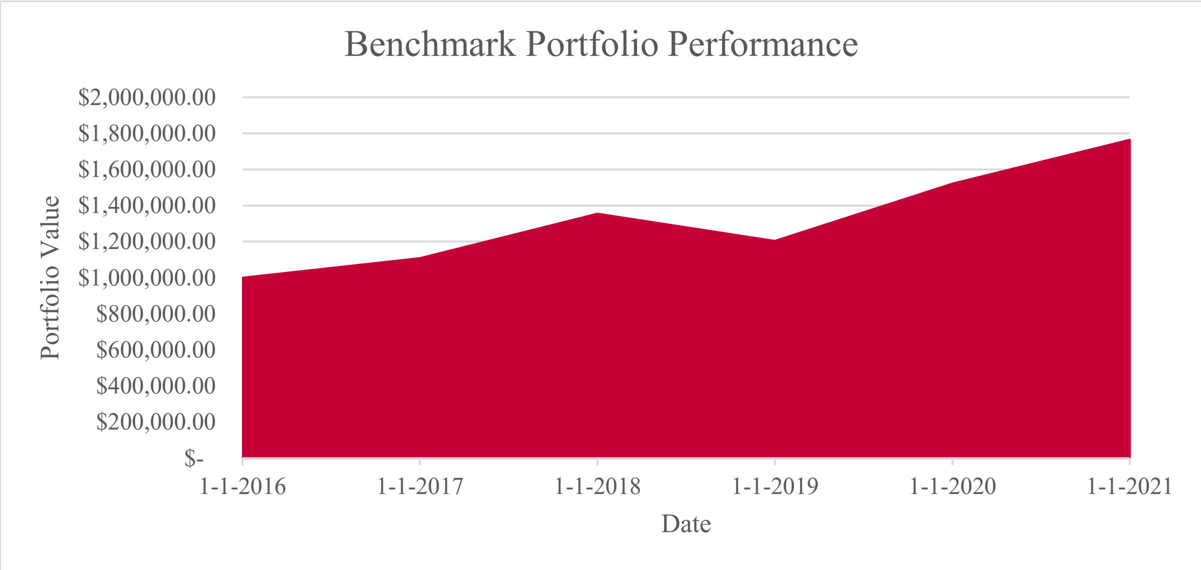


Figure 4: Benchmark portfolio performance

When one million dollars was invested at the beginning of 2016, and at the beginning of each upcoming year the amount obtained was reinvested in the new benchmark portfolio, the value of $1,000,000 would have increased to $1,764,482 at the end of 2020.

Table 21: Yearly portfolio value of benchmark portfolio

Date	Portfolio value
1-1-2016	$1,000,000
1-1-2017	$1,109,200
1-1-2018	$1,354,888
1-1-2019	$1,203,682
1-1-2020	$1,522,417
1-1-2021	$1,764,482

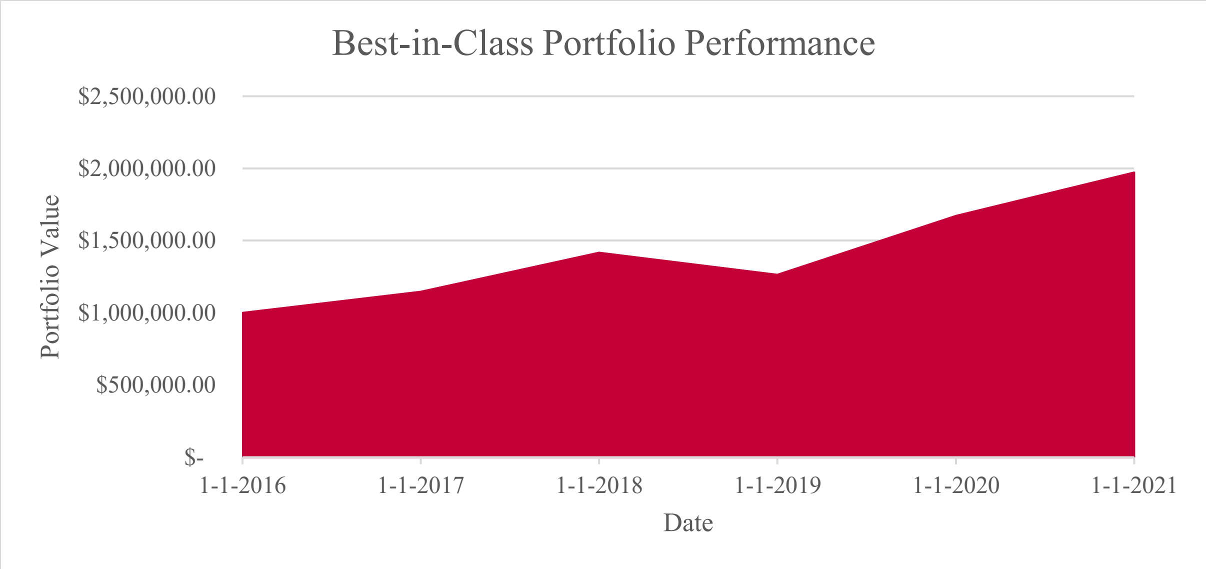


Figure 5: Best-in-class portfolio performance

When one million dollars was invested at the beginning of 2016, and at the beginning of each upcoming year the amount obtained at the end of the previous year was reinvested in the new BIC portfolio, the value of $1,000,000 would have increased to $1,972,054 at the end of 2020.

Table 22: Yearly portfolio value of best-in-class portfolio

Date	Portfolio value
1-1-2016	$1,000,000
1-1-2017	$1,145,790
1-1-2018	$1,416,998
1-1-2019	$1,264,529
1-1-2020	$1,670,949
1-1-2021	$1,972,054

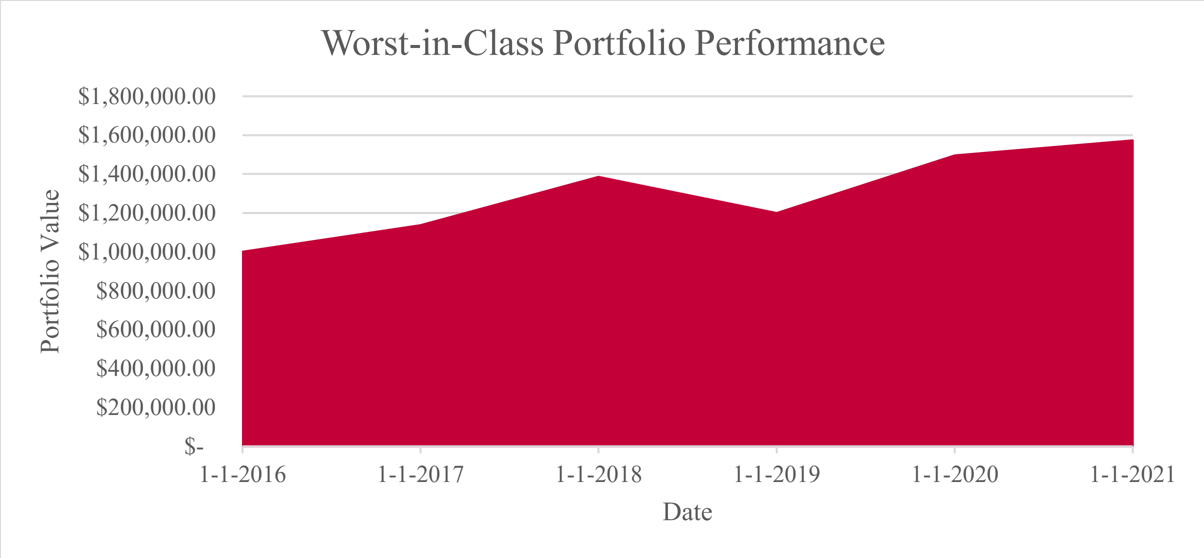


Figure 6: Worst-in-class portfolio performance

When one million dollars was invested at the beginning of 2016, and at the beginning of each upcoming year the amount obtained at the end of the previous year was reinvested in the new WIC portfolio, the value of $1,000,000 would have increased to $1,573,338 at the end of 2020.

Table 23: Yearly portfolio value of worst-in-class portfolio

Date	Portfolio value
1-1-2016	$1,000,000
1-1-2017	$1,136,500
1-1-2018	$1,386,189
1-1-2019	$1,199,747
1-1-2020	$1,496,564
1-1-2021	$1,573,338

In conclusion, following the strategy of the BIC portfolio would have yielded the highest return over the period 2016 to 2020. On the other hand, the WIC portfolio showed the lowest return over the period 2016 to 2020.

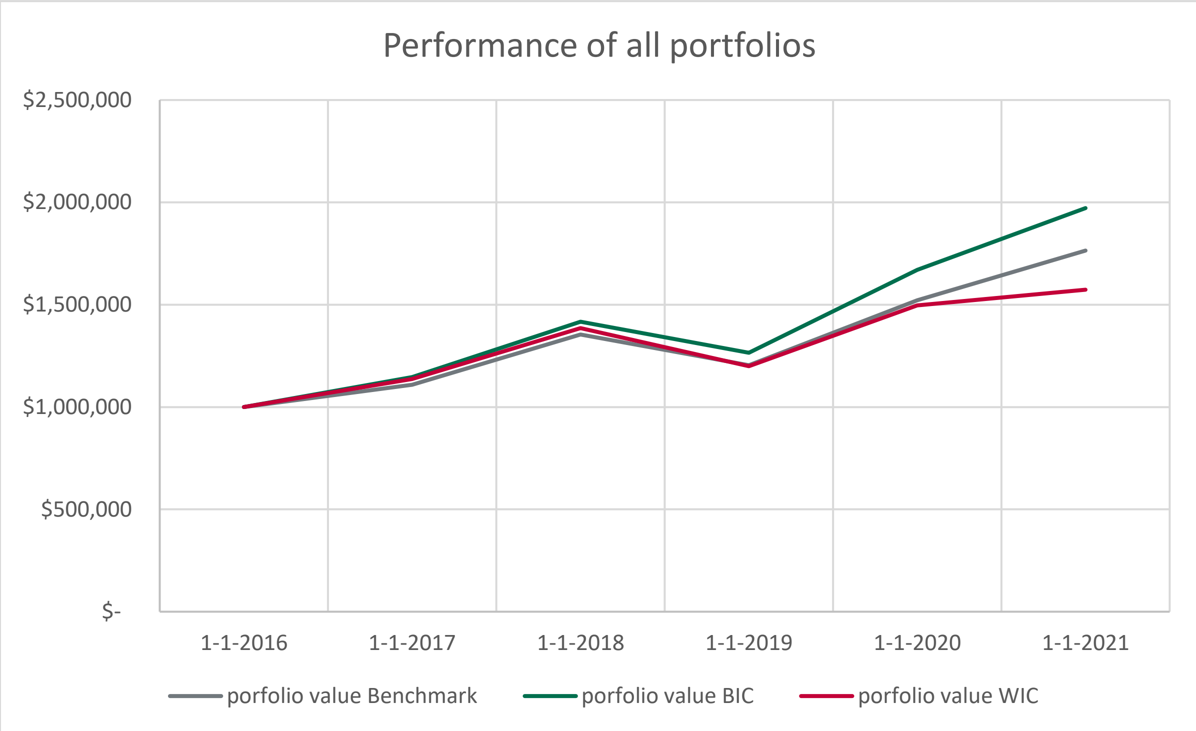


Figure 7: Performance of all portfolios

Figure 7 and Table 24 display the performance of the benchmark, BIC and WIC portfolios over the period 2016 to 2020. The strategy for each portfolio is to reinvest the obtained wealth every year according to the strategy of the portfolio. The starting values of the portfolios are set to $1,000,000 at the beginning of 2016. The obtained wealth of the benchmark, BIC and WIC portfolios are $1,764,482 and $1,972,054 and $1,573,338 respectively at the end of 2020.

Table 24: Yearly portfolio values of all portfolios

Date	Portfolio value benchmark	Portfolio value BIC	Portfolio value WIC
1-1-2016	$1,000,000	$1,000,000	$1,000,000
1-1-2017	$1,109,200	$1,145,790	$1,136,500
1-1-2018	$1,354,888	$1,416,998	$1,386,189
1-1-2019	$1,203,682	$1,264,529	$1,199,747
1-1-2020	$1,522,417	$1,670,949	$1,496,564
1-1-2021	$1,764,482	$1,972,054	$1,573,338

Figure 8 displays the monthly returns of the benchmark, BIC and WIC portfolios. The returns of the portfolios are shown from 1-1-2016 to 1-1-2021. From around 1-1-2019 the returns start to show more fluctuations. The monthly returns over time provide more insight into the short-term performances of the portfolios in comparison to the yearly data.

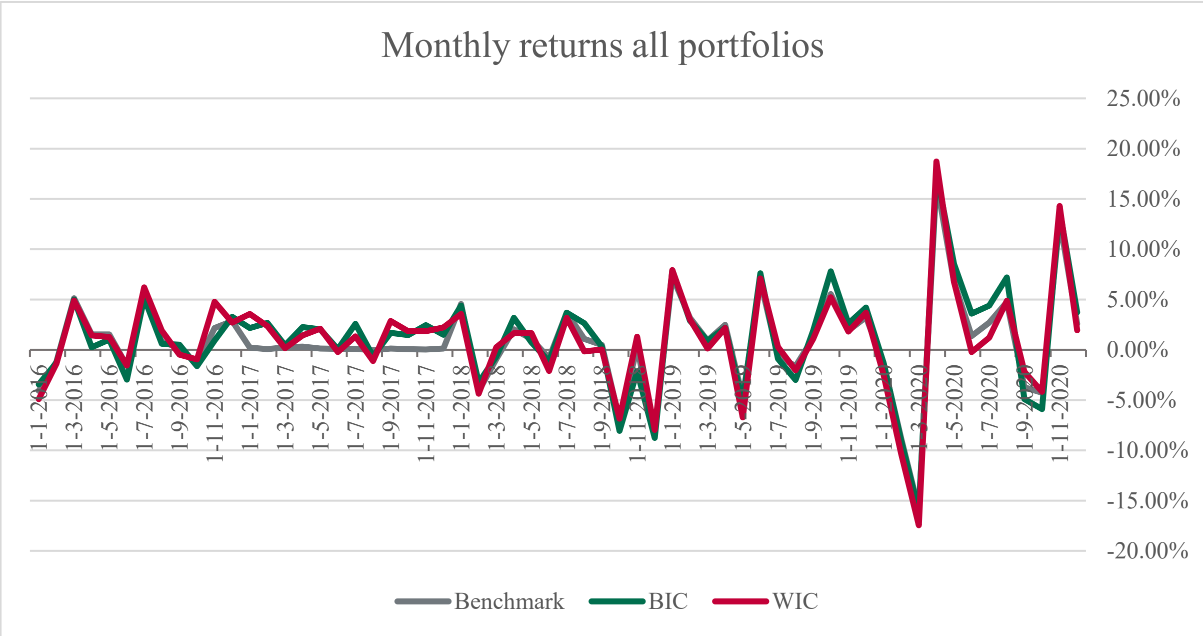


Figure 8: Monthly returns of all portfolios

Figure 9 displays the volatility of the benchmark, BIC and WIC portfolios over 1-1-2016 to 1-1-2021. The monthly calculated volatilities show a clear increase at the beginning of 2020, due to COVID-19. Besides, the monthly volatilities of the portfolios provide insight into the dispersion of the returns over the whole research period.

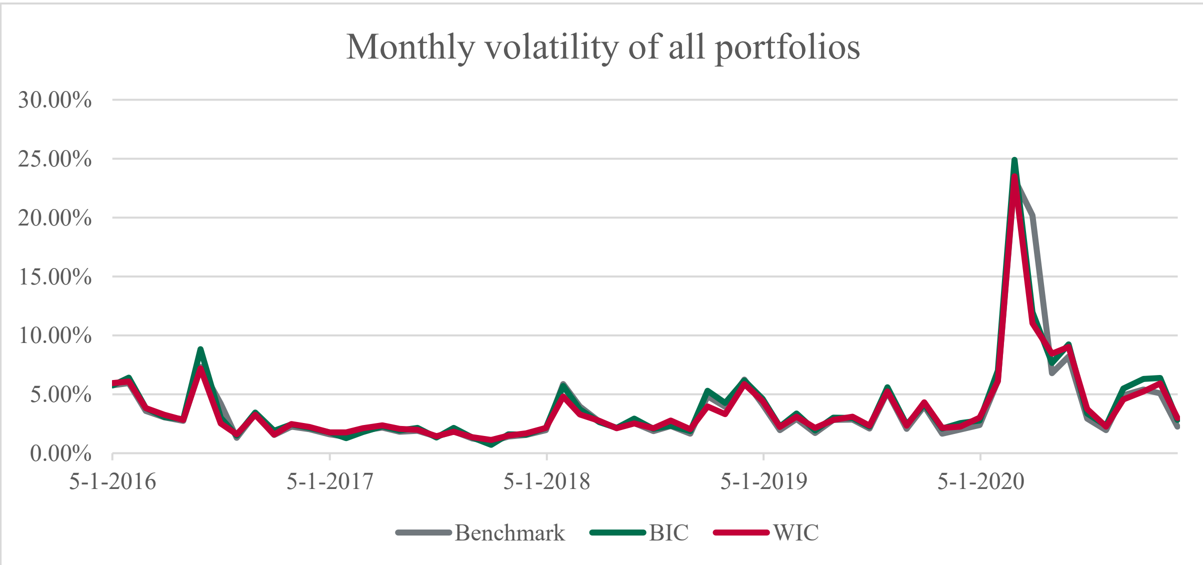


Figure 9: Monthly volatility of all portfolios

In the following paragraph, the risk adjusted-returns of the BIC and WIC portfolios are presented in graphs. The monthly calculated Sharpe, Sortino and Treynor ratios are visualised in order to spot whether the two datasets come from the same distribution.

Figure 10 displays the monthly Sharpe ratios of the BIC and WIC portfolios from 2016 to 2020. The trendline within the graph shows a linear relationship between the Sharpe ratios of the BIC and WIC portfolios. On the other hand, the points on the graph show some distance from the trendline. The graph shows that there is a difference in the outcomes of the Sharpe ratios of the BIC and WIC portfolios. The differences in the outcomes of the Sharpe ratios could mean that different returns were obtained for the units of risk taken.

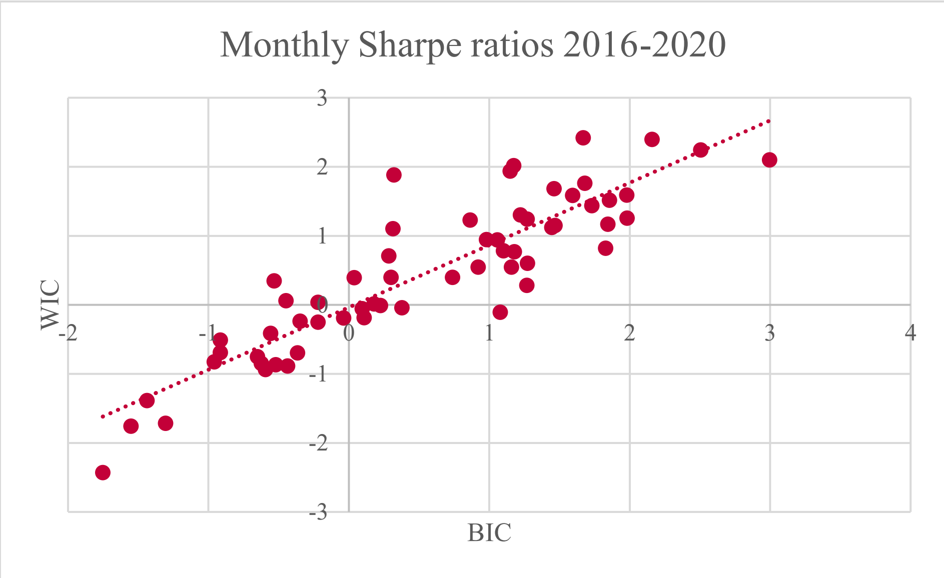


Figure 10: Monthly Sharpe ratios of BIC and WIC

Figure 11 displays the monthly Sortino ratios over the period 2016 to 2020. Also, the Sortino ratios of the BIC and WIC portfolios show a linear relationship. It seems as if the dispersion of the data points is less for the lower values of the Sortino ratios than the data of the Sharpe ratio.

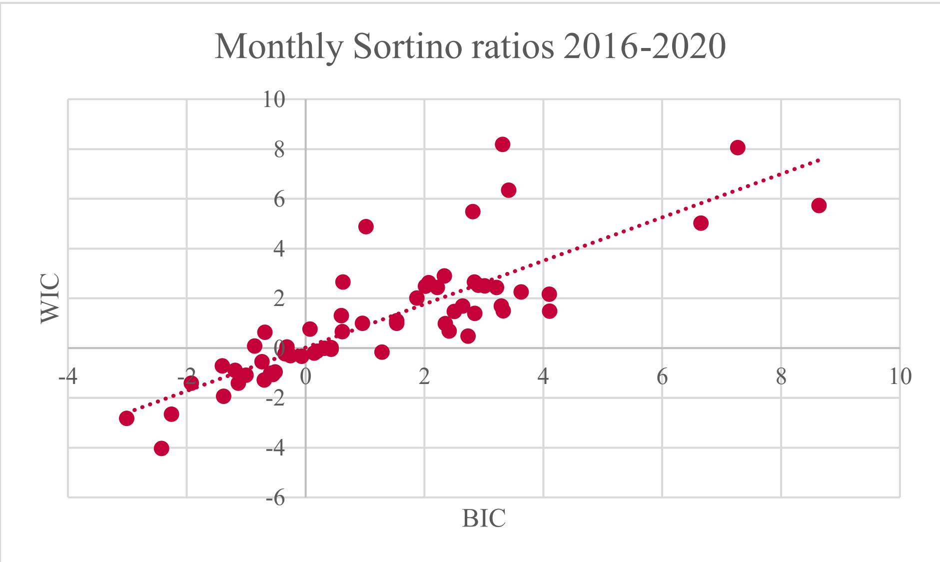


Figure 11: Monthly Sortino ratios of BIC and WIC

Figure 12 displays the monthly Treynor ratios of the BIC and WIC portfolios. The points on the graph have a smaller dispersion from the trendline than the Sharpe and Sortino ratios. These results of the dispersion considered to be small means that the Treynor ratios of the BIC and WIC portfolios are likely to be similar. Since the Treynor ratio takes the market risk into account, it can be concluded that for the return obtained by the BIC and WIC portfolios in proportion approximately the same level of systematic risk was taken.

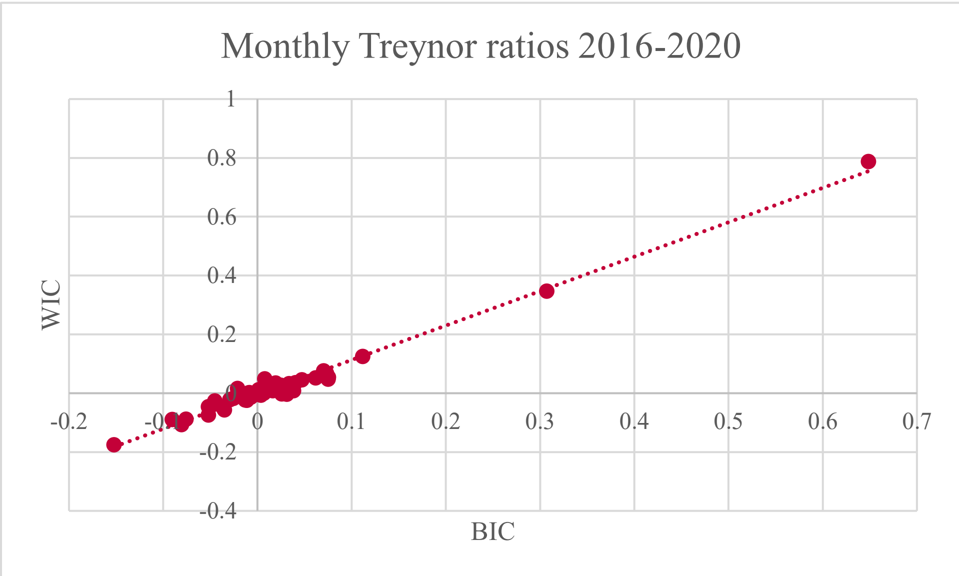


Figure 12: Monthly Treynor ratios of BIC and WIC

In order to gain insights into which strategy has the highest risk-adjusted returns monthly, several tables are provided. The tables display the number of times a portfolio shows the highest risk-adjusted returns in comparison to the other portfolios.

Table 25 displays the number of winning months per portfolio type. From 2016 to 2020 on a monthly basis, 60 data points of the Sharpe ratios have been calculated. The benchmark portfolios had the highest return for 20 out of the 60 months. The BIC portfolio had the highest Sharpe ratio 26 times. The WIC portfolio showed the lowest number of winning months.

Table 25: Number of winning months based on Sharpe ratios 2016-2020

Portfolio	**# winning months**	**% winning months**
Benchmark	20	33.33%
BIC	26	43.33%
WIC	14	23.33%

Table 26 displays the number of winning months per strategy based on the Sortino ratios from 2016 to 2020. The BIC portfolio had the highest number of winning months, namely 48.33% of the time it had the highest Sortino ratios. The benchmark portfolio showed the lowest number of winning months. The WIC portfolio had 16 winning months from a total of 60 months.

Table 26: Number of winning months based on Sortino ratios 2016-2020

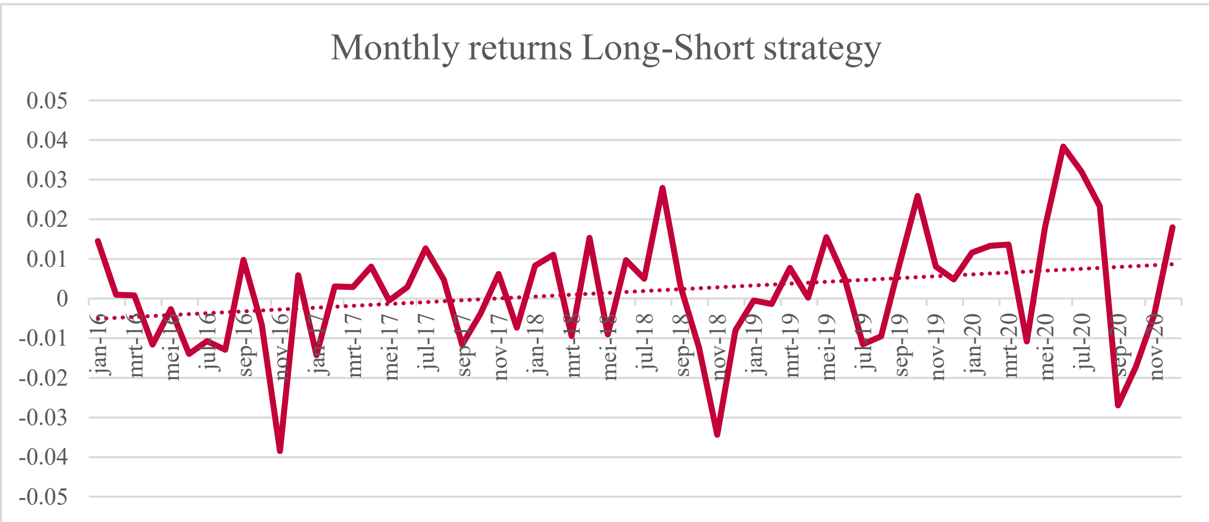
Portfolio	# winning months	% winning months
Benchmark	15	25.00%
BIC	29	48.33%
WIC	16	26.67%

Table 27 displays the number of winning months based on the Treynor ratios. The results for the winning months for the portfolios are the same as the Sharpe ratios. The benchmark had a winning rate of 33.33%. the BIC portfolio had the highest Treynor ratio 26 out of 60. The WIC portfolio showed a winning rate of 23.33%.

Table 27: Number of winning months based on Treynor ratios 2016-2020

Portfolio	# winning months	% winning months
Benchmark	20	33.33%
BIC	26	43.33%
WIC	14	23.33%

Figure 13 shows the monthly returns if a strategy of going long in the BIC strategy and going short in the WIC strategy was followed over 2016 to 2020. A positive monthly return of the Long-Short strategy would mean that the BIC portfolio has a better performance in terms of returns than the WIC



portfolio.

Figure 13: Monthly returns Long-Short strategy

Table 28: Number of winning and losing months for Long-Short Strategy

Year	# winning months	# losing months
2016	5	7
2017	7	5
2018	7	5
2019	8	4
2020	8	4
2016-2020	35	25

Table 28 shows the amount of winning and losing months of the Long-Short strategy for 2016-2020. When the number of winning months is substantially greater than the amount of losing months the strategy is considered to have a positive return. In 2016 the strategy had more losing than winning months, which means that the WIC performed better than the BIC portfolio. On the contrary, for the years 2017 to 2020, the number of winning months was greater than the losing months which indicates that over this period positive returns were obtained. In total, the Long-Short strategy had a total of 35 winning months and 25 losing months. All in all, Figure 13 and Table 28 show the returns and winning months respectively. The Long-Short strategy indicates that the BIC portfolio shows a better performance based on monthly returns than the WIC portfolio over the period 2016 to 2020.

6.5 Test of normality

In this section, the daily stock returns, weekly volatilities and the six metrics calculated monthly over the period 2016 to 2020 are tested for normality. The test for normality is required to know whether a parametric or non-parametric test applies to the results. For the test of normality, a Kolmogorov-Smirnov and Shapiro-Wilk test is performed. Moreover, the skewness and kurtosis are measured. Table 29 provides the conditions on whether the data is assumed to be normally distributed according to the Kolmogorov-Smirnov and Shapiro-Wilk tests, thereby the null hypothesis is mentioned.

Table 29: Null hypothesis and decisions on normality

Null hypothesis	Non-rejection Region	Rejection region	Significance level
The data are normally distributed	if p-value > α Decision: retain the null hypothesis	if p-value $\leq \alpha$ Decision: reject the null hypothesis	0.05

6.5.1 Normality tests of daily stock returns

In this section, the decision on whether the distributions are assumed to be normal are formed. The data is tested on normality with the help of the skewness and kurtosis of the data. Besides, the data is tested on normality with the Kolmogorov-Smirnov and Shapiro-Wilk tests. Table 30 provides the decisions based on the characteristics of the data. The tests are performed with a significance level of 0.05.

Table 30: Decisions on the normality of daily stock returns

Year	Portfolio type	Skewness z-value	Kurtosis z-value	Kolmogorov-Smirnov p-value	Shapiro-Wilk p-value	Normal assumption?
2016	benchmark	-4.141	20.655	0.000	0.000	No
	BIC	-7.788	26.432	0.000	0.000	No
	WIC	-6.609	17.068	0.000	0.000	No
2017	benchmark	0.761	5.065	0.004	0.004	No
	BIC	1.084	4.935	0.021	0.003	No
	WIC	0.419	4.424	0.200	0.016	No
2018	benchmark	-2.885	7.848	0.000	0.000	No
	BIC	-3.538	5.277	0.000	0.000	No
	WIC	-2.545	3.848	0.000	0.000	No
2019	benchmark	-3.506	12.152	0.000	0.000	No
	BIC	-2.949	10.006	0.002	0.000	No
	WIC	3.045	8.965	0.004	0.000	No
2020	benchmark	7.916	59.327	0.000	0.000	No
	BIC	-4.813	28.479	0.000	0.000	No
	WIC	-6.245	26.589	0.000	0.000	No
2016-2020	benchmark	23.571	367.357	0.000	0.000	No
	BIC	-15.100	173.486	0.000	0.000	No
	WIC	-18.914	159.857	0.000	0.000	No

For each of the portfolio types in each year no distribution of the daily stock returns is assumed to be normally distributed. The skewness and kurtosis z-values do not assume a normal distribution since values often are not within the boundaries of the interval -1.96 to 1.96. In addition, all the skewness, kurtosis, Kolmogorov-Smirnov and Shapiro-Wilk values indicate no normal distribution of the data except for the Kolmogorov-Smirnov test of the WIC and the skewness z-value of the benchmark, BIC and WIC portfolios of 2017. Therefore, no of the daily stock return data of the portfolios over the period 2016 to 2020 is assumed to be normally distributed.

6.5.2 Normality test of weekly volatility

In this section, normality tests are performed on the weekly volatility data. Over the research period of 2016 to 2020, all the weekly volatilities are calculated. Table 31 provides the information on the skewness, kurtosis, Kolmogorov-Smirnov test and Shapiro-Wilk test and finally, the decision on the normality of the data is given. The Kolmogorov-Smirnov test and Shapiro-Wilk test are performed with a confidence level of 0.05.

Table 31: Decision of the normality of weekly volatility data

Year	Portfolio type	Skewness z-value	Kurtosis z-value	Kolmogorov-Smirnov p-value	Shapiro-Wilk p-value	Normal assumption?
2016	benchmark	7.665	14.792	0.002	0.000	No
	BIC	10.100	24.509	0.000	0.000	No
	WIC	7.779	16.659	0.013	0.000	No
2017	benchmark	1.644	-0.117	0.200	0.241	Yes
	BIC	1.282	-0.337	0.200	0.317	Yes
	WIC	1.600	0.207	0.200	0.157	Yes
2018	benchmark	3.844	2.822	0.062	0.000	No
	BIC	3.174	1.548	0.009	0.003	No
	WIC	3.747	2.859	0.020	0.001	No
2019	benchmark	4.965	4.193	0.002	0.000	No
	BIC	5.056	4.970	0.003	0.000	No
	WIC	5.144	4.775	0.000	0.000	No
2020	benchmark	7.556	10.588	0.000	0.000	No
	BIC	6.921	10.142	0.000	0.000	No
	WIC	6.906	9.844	0.000	0.000	No
2016-2020	benchmark	32.859	106.523	0.000	0.000	No
	BIC	28.256	82.100	0.000	0.000	No
	WIC	29.391	89.042	0.000	0.000	No

Table 31 displays the z-values of the skewness and kurtosis. Moreover, the table shows the p-values of the Kolmogorov-Smirnov and Shapiro-Wilk tests. Based on the confidence level of 0.05, the z-values of the skewness and kurtosis must be within the interval of -1.96 to 1.96 and the Kolmogorov-Smirnov and Shapiro-Wilk test must show a p-value of greater than 0.05 to assume the data to be normally distributed. In 2017 the weekly volatilities of the benchmark, BIC and WIC portfolios are assumed to be normally distributed. On the contrary, in all other years, the values within the table do not show an indication of the weekly volatilities of the portfolios to be normally distributed.

6.5.3 Normality test of the six metrics based on monthly calculations

In this section, normality tests on the measures of return, volatility, Sharpe, Sortino, Treynor and carbon intensity are displayed. All these measures have been calculated monthly. The calculations resulted in 60 data points over the period 2016 to 2020 for each portfolio.

Table 32: Decision of the normality of all metrics

Years	Portfolio type	Metric	Skewness z-value	Kurtosis z-value	Kolmogorov-Smirnov p-value	Shapiro-Wilk p-value	Normal assumption?
2016-2020	benchmark	Return	-0.081	6.572	0.001	0.000	No
		Volatility	12.269	27.298	0.000	0.000	No
		Sharpe	0.906	-0.423	0.046	0.260	Yes
		Sortino	6.544	9.941	0.001	0.000	No
		Treynor	-0.809	6.572	0.001	0.000	No
		Carbon intensity	-1.515	-1.599	0.000	0.000	No
2016-2020	BIC	Return	-2.977	4.638	0.049	0.008	No
		Volatility	12.654	33.906	0.000	0.000	No
		Sharpe	-0.333	-1.252	0.051	0.277	Yes
		Sortino	2.482	1.781	0.200	0.018	No
		Treynor	14.408	43.378	0.000	0.000	No
		Carbon intensity	-2.913	-0.528	0.000	0.000	No
2016-2020	WIC	Return	-2.880	7.138	0.012	0.000	No
		Volatility	13.317	36.669	0.000	0.000	No
		Sharpe	-0.919	-0.628	0.200	0.536	Yes
		Sortino	2.874	2.089	0.010	0.005	No
		Treynor	15.819	49.781	0.000	0.000	No
		Carbon intensity	-2.615	-1.674	0.000	0.000	No

Table 32 displays all values on which the assumption of normality is based. For all distributions of the metrics except for the Sharpe ratio, the data is assumed not to be normally distributed.

6.6 Statistical significance

In this section, the statistical significance of the distributions of the daily stock returns of the benchmark, BIC and WIC portfolios are examined. Furthermore, the statistical significance of the weekly volatility is tested. Besides, the statistical significance of the six metrics on a yearly and monthly basis is determined. Table 33 displays the null hypothesis and the decisions based on the outcome of the p-values.

Table 33: Null-hypothesis and decisions on significance

Null hypothesis	Non-rejection region	Rejection region	Significance level
The distributions of the three portfolios are the same	if p-value > α Decision: retain the null hypothesis	if p-value ≤ α Decision: reject the null hypothesis	0.05

Table 34 provides a summary of the tests that are used when the data was assumed to be normally distributed or not. The daily stock returns of the benchmark, BIC and WIC portfolios are assumed not to be normally distributed over the period 2016 to 2020, therefore non-parametric tests are performed. Besides, the weekly volatility data of 2016, and 2018 to 2020, and the distributions of the monthly measured six measures except for the Sharpe ratio are assumed not to be normally distributed. All other distributions are assumed to be normally distributed. When the data is assumed to be normally distributed the one-way ANOVA test is performed, and when the data is assumed not to be normally distributed the Kruskal-Wallis test is performed.

Table 34: Summary of statistical hypothesis tests to be used

Distribution	Year(s)	Normally distributed assumption?	Test	Parametric / Non-parametric test
Daily stock return data of benchmark, BIC and WIC	2016-2020	No	Kruskal-Wallis Test	Non-parametric test
Weekly volatility data of benchmark BIC and WIC	2016, 2018-2020	No	Kruskal-Wallis Test	Non-parametric test
	2017	Yes	One-way ANOVA	Parametric
Distribution of monthly measured Return, Volatility, Sortino, Treynor, Carbon Intensity of benchmark, BIC and WIC	2016-2020	No	Kruskal-Wallis Test	Non-parametric test
Distribution of Sharpe measured monthly of benchmark, BIC and WIC	2016-2020	Yes	One-way ANOVA	Parametric

6.6.1 Statistical significance of daily stock returns

All the daily stock return distributions are considered to not be normally distributed, which means that a non-parametric test can be used on the data. The differences in the distributions of the daily stock returns over the years 2016 to 2020 have been tested with a Kruskal-Wallis test. This test was used since it does not assume an underlying distribution of the data and it can be used for three or more related samples. The test on the distributions of the three portfolio types is executed to check whether the relationship between the three portfolios is engendered by something other than chance alone. Table 35 presents the outcome of the statistical hypothesis test on the daily stock returns over the years 2016 to 2020.

Table 35: Significance test of daily stock returns

Year	Null hypothesis	Test	P-value	Decision
2016	The distributions of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.757	Retain the null hypothesis
2017	The distributions of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.998	Retain the null hypothesis
2018	The distributions of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.885	Retain the null hypothesis
2019	The distributions of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.976	Retain the null hypothesis
2020	The distributions of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.901	Retain the null hypothesis
2016-2020	The distributions of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.968	Retain the null hypothesis

The Kruskal-Wallis tests did not lead to the decision of rejecting the null hypothesis of the three portfolio types to be the same for any year nor the whole research period. The outcome of the decision engenders the decision of retaining the null hypothesis of the distributions of the daily stock returns of the three different investment portfolios to be the same of all individual years and the total period.

6.6.2 Statistical significance of weekly volatility

In this section, the weekly volatility of the benchmark, BIC and WIC portfolio over the years 2016 to 2020 is tested with Kruskal-Wallis Test and the one-way ANOVA. The combinations of distributions that are tested are the combination of all three different portfolios together. Table 36 shows the outcome of the tests with the designated year. For years 2016 to 2020, the null hypothesis of the combination of the three distributions of the weekly volatility data is decided to be retained.

Table 36: Significance test of weekly volatilities

Year	Null hypothesis	Test	P-value	Decision
2016	The distributions of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.787	Retain the null hypothesis
2017	The distributions of the benchmark, BIC & WIC are the same	One-way ANOVA	0.603	Retain the null hypothesis
2018	The distributions of the benchmark, BIC & WIC are the same	Kruskal-Wallis Test	0.965	Retain the null hypothesis
2019	The distributions of the benchmark, BIC & WIC are the same	Kruskal-Wallis Test	0.421	Retain the null hypothesis
2020	The distributions of the benchmark, BIC & WIC are the same	Kruskal-Wallis Test	0.678	Retain the null hypothesis
2016-2020	The distributions of the benchmark, BIC & WIC are the same	Kruskal-Wallis Test	0.401	Retain the null hypothesis

6.6.3 Statistical significance of yearly data

To test the significance of all the yearly measured six metrics, a test for small sample sizes is used. To test the significance of the five data points per metric the t-test equality of means is used. Each metric has five data points in total since there is one data point measured each year from 2016 to 2020. In this section, the differences between the benchmark & BIC and the BIC & WIC are tested for significance. Table 37 and Table 38 display the metrics and the appurtenant p-values of the statistical tests. For all metrics, except the carbon intensity, the null hypothesis was retained with a significance level of 0.05 for the tested combinations.

Table 37: Significance test of benchmark and BIC portfolios

Years	Null hypothesis	Test	p-value	Decision
2016-2020	The distributions of the return of the benchmark and BIC are the same	T-test equality of means	0.922	Retain the null hypothesis
2016-2020	The distributions of the volatility of the benchmark and BIC are the same	T-test equality of means	0.976	Retain the null hypothesis
2016-2020	The distributions of the Sharpe of the benchmark and BIC are the same	T-test equality of means	0.981	Retain the null hypothesis
2016-2020	The distributions of the Sortino of the benchmark and BIC are the same	T-test equality of means	0.951	Retain the null hypothesis
2016-2020	The distributions of the Treynor of the benchmark and BIC are the same	T-test equality of means	0.898	Retain the null hypothesis
2016-2020	The distributions of the carbon intensity of the benchmark and BIC are the same	T-test equality of means	0.000	Reject the null hypothesis

Table 38: Significance test of BIC and WIC portfolios

Years	Null hypothesis	Test	p-value	Decision
2016-2020	The distributions of the return of the BIC and WIC are the same	T-test equality of means	0.743	Retain the null hypothesis
2016-2020	The distributions of the volatility of the BIC and WIC are the same	T-test equality of means	0.923	Retain the null hypothesis
2016-2020	The distributions of the Sharpe of the BIC and WIC are the same	T-test equality of means	0.856	Retain the null hypothesis
2016-2020	The distributions of the Sortino of the BIC and WIC are the same	T-test equality of means	0.842	Retain the null hypothesis
2016-2020	The distributions of the Treynor of the BIC and WIC are the same	T-test equality of means	0.714	Retain the null hypothesis
2016-2020	The distributions of the carbon intensity of the BIC and WIC are the same	T-test equality of means	0.000	Reject the null hypothesis

6.6.4 Statistical significance of monthly data

Additional significance tests are performed with data measured monthly. In this way, a sample of 60 data points was gathered for all six measures within the five research periods. Since the carbon intensity was provided as yearly data, the assumption to split this data up in months is assumed. This assumption would imply that the carbon emissions are evenly emitted on a monthly basis over a whole year. Besides, the same sort of assumption must be made for the achieved yearly revenue that is assumed to be evenly obtained monthly. Since the data of the carbon intensity is calculated with the two above variables, these assumptions had to be made to be able to arrive at a number of data points on a monthly basis.

Table 39 displays the results of the hypothesis tests for the six measures on the benchmark, BIC and WIC portfolios measured monthly. On each distribution of the data, a Kruskal Wallis test was performed except for the Sharpe ratio. Only the null hypothesis for the distributions of the carbon intensity of the benchmark, BIC and WIC portfolios was rejected, all other null hypotheses were retained.

Table 39: Significance test of all measures 2016-2020

Years	Null hypothesis	Test	p-value	Decision
2016-2020	The distributions of the return of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.653	Retain the null hypothesis
2016-2020	The distributions of the volatility of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.586	Retain the null hypothesis
2016-2020	The distributions of the Sharpe of the benchmark, BIC and WIC are the same	One-way ANOVA	0.535	Retain the null hypothesis
2016-2020	The distributions of the Sortino of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.545	Retain the null hypothesis
2016-2020	The distributions of the Treynor of the benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.636	Retain the null hypothesis
2016-2020	The distributions of the carbon intensity of benchmark, BIC and WIC are the same	Kruskal-Wallis Test	0.000	Reject the null hypothesis

6.7 Conclusion

Chapter 6 provided the performance results of the benchmark, BIC and WIC portfolio from 2016 to 2020. In 2016 the WIC portfolio performed the best in terms of both returns and risk-adjusted returns. The BIC portfolio showed the worst return and risk-adjusted returns in 2016. On the other hand, for the period 2017 to 2020, the BIC portfolios performed the best for both the return and risk-adjusted returns. Besides, this chapter showed the results of the normality tests and the statistical hypothesis testing for the period of 2016 to 2020 of the daily stock returns, the weekly volatility, the yearly measured metrics and the monthly measured metrics. The Kruskal-Wallis test and the One-way ANOVA were performed on the data that was assumed to be non-parametric and parametric respectively. Only the null hypothesis on the carbon intensities of the benchmark, BIC and WIC distributions to be the same was rejected. All other null hypotheses on the distributions of the benchmark, BIC and WIC were retained.

7 Conclusion

In this chapter, a conclusion on the research is given. In addition, a discussion of the results is provided. Moreover, the contributions to the theory and practices are discussed. Besides, the limitations of the study are reviewed. Lastly, recommendations for future research are provided.

7.1 Conclusion

The objective of this master thesis is to answer the research question: "*Do investment portfolios with a low carbon intensity show higher risk-adjusted returns than portfolios with a higher carbon intensity?*" In order to answer this main research question, a literature review was executed and analysis methods were studied. The outcome is the creation of benchmark, best-in-class and worst-in-class portfolios based on carbon intensity over the period 2016 to 2020.

The datasets that have been combined are carbon emission data, the MSCI World index allocation and the adjusted close price data of the stocks within the portfolios. During the construction of the portfolios data has been filtered and all the different currencies from the stocks within the portfolios were converted to U.S. Dollars. The MSCI World Index has been set as the benchmark portfolio. The best-in-class and worst-in-class portfolios were derived from this benchmark portfolio. The best-in-class portfolios contain the top best performing twenty per cent stocks of each sector based on their carbon intensity. Furthermore, the worst-in-class portfolios contain the worst-performing twenty per cent stocks of each sector based on their carbon intensity. These three different investment portfolios were tested on their return, volatility, Sharpe ratio, Sortino ratio and Treynor ratio for each year over the period 2016 to 2020. Additionally, Value at Risk calculations were provided for each strategy to obtain insights into the risk of the investment portfolios.

The answer to the main research questions is that historically, the BIC portfolios from 2017 to 2020 showed the highest returns and risk-adjusted returns. In 2016 the WIC portfolio performed the best in terms of return, volatility and risk-adjusted returns. On average for 2016 to 2020, the BIC portfolio showed a historical return of 13.86% and the benchmark and WIC portfolio showed an average of 12.86% and 10.41% respectively. In terms of the risk-adjusted returns over the period 2016 to 2020, the Sharpe ratio of the BIC was on average 1.253. The Sharpe ratio of the benchmark and WIC portfolio were 1.224 and 1.036 respectively.

This master thesis also helps to solve the core problem of the company for which this thesis is executed. The core problem was that the company did not have sufficient insight into the influence of ESG investing on investment portfolios. With the help of insights and findings obtained from this master thesis, more insight into one aspect of ESG investing was obtained.

7.2 Discussion

In this section, a discussion is given. The discussion includes the contributions to the theory and practice. Further, an elaboration is provided on how the empirical findings of this research can support management decisions which answers research question 4. Besides, the limitations of this research are presented.

7.2.1 Contributions to theory and practice

With the help of this study, an extension of the existing literature is provided with insights into the impact of carbon intensity on the historical performances of investment portfolios. Research question 4 is: *How can the empirical findings be translated into decision support?* The empirical findings of this master thesis provide practical knowledge that can be employed for future decisions of investment managers. Since investment managers need to consider ESG related questions into their investment portfolios for reputation and policies, it is important to know what effects carbon emissions could have on their investment portfolios. Shifts in focus on responsible investing bring the need for insights into the possible effects. Although outstanding historical performances do not necessarily guarantee future successes, insights into historical performances can help with creating scenario analyses and with what risk to consider in future investments. Besides, the adoption of responsible investments can have profound benefits on people and the planet. Moreover, considering carbon intensity or ESG factors means focusing on the long-term instead of short-term benefits. All things considered, the consideration of carbon emission of investment portfolios by managers can lead to promising performances and could stimulate improving environmental impacts of investments.

The contributions of this research to the current body of knowledge are the insights into the effect that the carbon intensity had on investment portfolios in the past. Existing literature shows different insights into the effect of carbon emissions on investments. Some literature shows that carbon emission is seen as risky which should display higher returns. On the other hand, literature states that after the Paris Agreement low carbon emissions are considered less risky. In this master thesis, the observed results show that on a risk-adjusted basis the low carbon intensity portfolios performed better over the period 2017 to 2020. Since this research was done on data after the Paris Agreement, which was entered into force on 4 November 2016, a discussion can be held whether this influenced the obtained results. Moreover, it seems that there is more and more awareness by investors on climate change and this could lead to a shift in investors choosing more responsible investment options.

In conclusion, the results and outcome of this research form a great set of insights on the topic of sustainable investing. The results of the carbon emission-based strategies provide more clarity about the impact of ESG investing on investment portfolios. The promising results of the best-in-class portfolios show the potential for financial institutions of implementing green investment strategies. Furthermore, this research fills a salient gap in terms of the influence of carbon intensity on investment portfolios. Moreover, the results build on the existing literature by providing empirical findings on the topic of ESG investing. Besides, this research redounds to society since investing in a green way stimulates companies to go greener which helps to sustain the quality of life for future generations.

7.2.2 Limitations

In this section, the limitations of the research are described. First, the data on the carbon intensity was provided yearly. This means that only yearly numbers of companies are provided about their revenues and carbon emissions. The yearly numbers of the carbon intensity limit down the research to yearly analysis. Nevertheless, assumptions on these data can be made to research a narrower time frame.

Second, from the data received from Sustainalytics not all carbon emission values were reported by companies, which means that a certain percentage of the carbon emission values are estimated by Sustainalytics. In literature, discussions are already formed about this topic since the estimated values by rating agencies are subjective.

Third, the benchmark, BIC and WIC portfolios are constructed as identical as possible except for the carbon intensity, to let the effect of the carbon intensity on the performances of the investment portfolios arise. The focus of creating similar portfolios was on a sector basis, this means that in terms of countries within the different portfolios differences can be seen in the weight per country.

In summary, biases in the results could stem from the estimated values of Sustainalytics that are subjective and the extent to which the benchmark, BIC and WIC portfolios are identical except for their carbon intensity.

7.3 Recommendations for future research

For future research, a higher percentage of reported values on carbon emissions should be obtained to decrease subjectivity on these values. Moreover, different strategies based on carbon intensity could be investigated. In this research, the top and bottom twenty per cent performers based on carbon intensity were used to construct investment portfolios, but other percentages can be employed.

Furthermore, if the market capitalisation of firms is known, different groups can be created based on both firm sizes and carbon intensity to test whether firm size in terms of market capitalisation has an impact on the returns and risk-adjusted returns of investment portfolios. Besides, a more extensive set of sectors could be used to obtain a more in-depth sector allocation of the stocks within a portfolio. Further research could also employ investment portfolios created from carbon intensity calculated based on Scope 1, Scope 2 and Scope 3 emissions both separated and combined.

Additionally, research on the characteristic of firms considered with a low or high carbon intensity could be conducted to obtain knowledge of whether firms with a low carbon intensity would also perform better on fundamentals such as income statements, balance sheets and cash flow statements. Since carbon intensity is only one factor of the environmental pillar of ESG, wider research could be done into the effect of more variables that belong to the environmental pillar of ESG such as water stress, biodiversity toxic emissions and waste. Also, a broader investigation into all three pillars of ESG could be done to see what themes have the greatest impact on the return and risk of investment portfolios. Moreover, a wider time frame could be investigated since this research focused on the period 2016 to 2020.

References

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal, 74*(3), 87-103.

Aparicio, F. M., & Estrada, J. (2001). Empirical distributions of stock returns: European securities markets, 1990-95. *The European Journal of Finance, 7*(1), 1-21.

Bacon, C. R. (2008). *Practical portfolio performance measurement and attribution* (Vol. 546): John Wiley & Sons.

Bassen, A., & Kovacs, A. M. M. (2008). Environmental, social and governance key performance indicators from a capital market perspective. *Zeitschrift für Wirtschafts-und Unternehmensethik*(9/2), 182-192.

Berry, T. C., & Junkus, J. C. (2013). Socially responsible investing: An investor perspective. *Journal of business ethics, 112*(4), 707-720.

Blanco, R., Brennan, S., & Marsh, I. W. (2004). An empirical analysis of the dynamic relationship between investment grade bonds and credit default swaps.

Bodansky, D. (2001). The history of the global climate change regime. *International relations and global climate change, 23*(23), 505.

Bodansky, D. (2016). The legal character of the Paris Agreement. *Review of European, Comparative & International Environmental Law, 25*(2), 142-150.

Böhringer, C. (2003). The Kyoto protocol: a review and perspectives. *Oxford Review of Economic Policy, 19*(3), 451-466.

Bolton, P., & Kacperczyk, M. (2020a). *Do investors care about carbon risk?* (0898-2937). Retrieved from

Bolton, P., & Kacperczyk, M. T. (2020b). Carbon premium around the world.

Bugg-Levine, A., & Emerson, J. (2011). Impact investing: Transforming how we make money while making a difference. *Innovations: Technology, Governance, Globalization, 6*(3), 9-18.

Burton, I. (1987). Report on reports: Our common future: The world commission on environment and development. *Environment: Science and Policy for Sustainable Development, 29*(5), 25-29.

Bushnell, J. B., Chong, H., & Mansur, E. T. (2013). Profiting from regulation: Evidence from the European carbon market. *American Economic Journal: Economic Policy, 5*(4), 78-106.

Cheung, Y. H., & Powell, R. J. (2012). Anybody can do value at risk: a nonparametric teaching study. *Australasian Accounting, Business and Finance Journal, 6*(1), 111-123.

Christensen, D., Serafeim, G., & Sikochi, A. (2019). *Why is corporate virtue in the eye of the beholder? The case of ESG ratings*. Retrieved from

Clark, W. C. (1989). Managing planet earth. In *Global Climate Change* (pp. 1-12): Springer.

Clarkin, J. E., & Cangioni, C. L. (2016). Impact investing: A primer and review of the literature. *Entrepreneurship Research Journal, 6*(2), 135-173.

Cole, M. A., Elliott, R. J., Okubo, T., & Zhou, Y. (2013). The carbon dioxide emissions of firms: A spatial analysis. *Journal of Environmental Economics and Management, 65*(2), 290-309.

Compact, U. G. (2004). Who cares wins: Connecting financial markets to a changing world. *New York*.

Cornell, B. (2021). ESG preferences, risk and return. *European Financial Management, 27*(1), 12-19. doi:10.1111/eufm.12295

Damodaran, A. (1999). Estimating risk free rates. *WP, Stern School of Business, New York*.

De, I., & Clayman, M. R. (2015). The benefits of socially responsible investing: An active manager's perspective. *The Journal of Investing, 24*(4), 49-72.

Eccles, R. G., Ioannou, I., & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. *Management Science, 60*(11), 2835-2857.

Fulton, M., Kahn, B., & Sharples, C. (2012). Sustainable investing: Establishing long-term value and performance. *Available at SSRN 2222740*.

Gazheli, A., Van Den Bergh, J., & Antal, M. (2016). How realistic is green growth? Sectoral-level carbon intensity versus productivity. *Journal of Cleaner Production, 129*, 449-467.

Gibson, R., Krueger, P., & Schmidt, P. S. (2019). ESG rating disagreement and stock returns. *Swiss Finance Institute Research Paper*(19-67).

Giese, G., Lee, L.-E., Melas, D., Nagy, Z., & Nishikawa, L. (2017). Foundations of ESG investing. *MSCI ESG Research LLC. MSCI inc. PDF Retrieved April, 27*, 2020.
Halbritter, G., & Dorfleitner, G. (2015). The wages of social responsibility—where are they? A critical review of ESG investing. *Review of Financial Economics, 26*, 25-35.
Heerkens, H., & van Winden, A. (2017). *Solving managerial problems systematically*: Noordhoff.
Hill, J. (2020). *Environmental, Social, and Governance (ESG) investing: A balanced analysis of the theory and practice of a sustainable portfolio*: Academic Press.
Hoffmann, V. H., & Busch, T. (2008). Corporate carbon performance indicators: Carbon intensity, dependency, exposure, and risk. *Journal of Industrial Ecology, 12*(4), 505-520.
Hong, H., & Kostovetsky, L. (2012). Red and blue investing: Values and finance. *Journal of financial economics, 103*(1), 1-19.
Houweling, P., & Vorst, T. (2002). An empirical comparison of default swap pricing models. *ERIM Report Series Reference No. ERS-2002-23-F&A*.
Hull, J. (2012). *Risk management and financial institutions,+ Web Site* (Vol. 733): John Wiley & Sons.
Hull, J., Predescu, M., & White, A. (2004). The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of banking & finance, 28*(11), 2789-2811.
Jacobsen, R. (1988). The persistence of abnormal returns. *Strategic management journal, 9*(5), 415-430.
Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. *The Journal of Finance, 23*(2), 389-416.
Kaiser, L. (2020). ESG integration: Value, growth and momentum. *Journal of Asset Management, 21*(1), 32-51.
Kempf, A., & Osthoff, P. (2007). The effect of socially responsible investing on portfolio performance. *European Financial Management, 13*(5), 908-922.
Koch, N., & Bassen, A. (2013). Valuing the carbon exposure of European utilities. The role of fuel mix, permit allocation and replacement investments. *Energy economics, 36*, 431-443.
Kumar, P., & Firoz, M. (2018). Corporate carbon intensity matter: predicting firms' financial performance. *SCMS Journal of Indian Management, 15*(4), 74-74.
Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy economics, 34*(1), 215-226.
Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance, 72*(2), 853-910.
Linter, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics, 47*(1), 13-37.
Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383-417.
Mănescu, C. (2011). Stock returns in relation to environmental, social and governance performance: Mispricing or compensation for risk? *Sustainable development, 19*(2), 95-118.
Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7*(1), 77-91. doi:10.2307/2975974
McLEOD, W., & van Vuuren, G. (2004). Interpreting the Sharpe ratio when excess returns are negative. *Investment Analysts Journal, 33*(59), 15-20.
Modigliani, F., & Leah, M. (1997). Risk-adjusted performance. *Journal of portfolio management, 23*(2), 45.
Mohan, V., Singh, J. G., & Ongsakul, W. (2016). Sortino ratio based portfolio optimization considering EVs and renewable energy in microgrid power market. *IEEE Transactions on Sustainable Energy, 8*(1), 219-229.
Monasterolo, I., & De Angelis, L. (2020). Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecological Economics, 170*, 106571.
Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the econometric society*, 768-783.
Nandy, S. (2014). A quantitative comparison of the financial returns of index ETFs and matched index mutual funds. *International Journal of Business and Management, 9*(7), 10.

Narayan, P. K., & Sharma, S. S. (2015). Is carbon emissions trading profitable? *Economic Modelling, 47*, 84-92.
Nilsson, J. (2008). Investment with a conscience: Examining the impact of pro-social attitudes and perceived financial performance on socially responsible investment behavior. *Journal of business ethics, 83*(2), 307-325.
Oberndorfer, U. (2009). EU emission allowances and the stock market: evidence from the electricity industry. *Ecological Economics, 68*(4), 1116-1126.
Oestreich, A. M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme. *Journal of banking & finance, 58*, 294-308.
Officer, R. R. (1972). The distribution of stock returns. *Journal of the american statistical association, 67*(340), 807-812.
Panna, M. (2017). Note on simple and logarithmic return. *APSTRACT: Applied Studies in Agribusiness and Commerce, 11*(1033-2017-2935), 127-136.
Puaschunder, J. M. (2016). On the emergence, current state, and future perspectives of Socially Responsible Investment (SRI). *Consilience*(16), 38-63.
Renneboog, L., Ter Horst, J., & Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of banking & finance, 32*(9), 1723-1742.
Richter, P. M., & Schiersch, A. (2017). CO2 emission intensity and exporting: Evidence from firm-level data. *European Economic Review, 98*, 373-391.
Rollinger, T. N., & Hoffman, S. T. (2013). Sortino: a 'sharper'ratio. *Chicago, IL: Red Rock Capital. http://www. redrockcapital. com/assets/RedRock_Sortino_white_paper. pdf.*
Rom, B. M., & Ferguson, K. W. (1994). Post-modern portfolio theory comes of age. *Journal of Investing, 3*(3), 11-17.
Ross, S., Westerfield, R., & Jaffe, J. (2002). Capital market theory: An overview. *Corporate finance, 6*, 226-247.
Sahut, J.-M., & Pasquini-Descomps, H. (2015). ESG impact on market performance of firms: International Evidence. *Management International/International Management/Gestiòn Internacional, 19*(2), 40-63.
Salaber, J. M. (2007). *The determinants of sin stock returns: Evidence on the European market.* Paper presented at the Paris December 2007 Finance International Meeting AFFI-EUROFIDAI Paper.
Scholz, H., & Wilkens, M. (2005). Investor-specific performance measurement: A justification of sharpe ratio and treynor ratio. *International Journal of Finance, 17*(4), 3671.
Schueth, S. (2003). Socially responsible investing in the United States. *Journal of business ethics, 43*(3), 189-194.
Serafeim, G., & Yoon, A. (2021). Stock Price Reactions to ESG News: The Role of ESG Ratings and Disagreement. *Harvard Business School Accounting & Management Unit Working Paper*(21-079).
Sharifzadeh, M., & Hojat, S. (2012). An analytical performance comparison of exchange-traded funds with index funds: 2002–2010. *Journal of Asset Management, 13*(3), 196-209.
Sharpe, W. F. (1964). CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK. *The Journal of Finance, 19*(3), 425-442. doi:10.1111/j.1540-6261.1964.tb02865.x
Sharpe, W. F. (1966). Mutual fund performance. *The Journal of business, 39*(1), 119-138.
Sharpe, W. F. (1994). The sharpe ratio. *Journal of portfolio management, 21*(1), 49-58.
Siddikee, M. N. (2018). Effect of daily dividend on arithmetic and logarithmic return. *The Journal of Finance and Data Science, 4*(4), 247-272.
Sinha, P., Schew, W. A., Sawant, A., Kolwaite, K. J., & Strode, S. A. (2010). Greenhouse gas emissions from US institutions of higher education. *Journal of the Air & Waste Management Association, 60*(5), 568-573.
Sortino, F. A., & Price, L. N. (1994). Performance measurement in a downside risk framework. *The Journal of Investing, 3*(3), 59-64.
Soytas, U., Sari, R., & Ewing, B. T. (2007). Energy consumption, income, and carbon emissions in the United States. *Ecological Economics, 62*(3-4), 482-489.

Statman, M. (2006). Socially responsible indexes. *The Journal of Portfolio Management, 32*(3), 100-109.
Statman, M., & Glushkov, D. (2009). The wages of social responsibility. *Financial Analysts Journal, 65*(4), 33-46.
Streck, C., Keenlyside, P., & Von Unger, M. (2016). The Paris Agreement: a new beginning. *Journal for European Environmental & Planning Law, 13*(1), 3-29.
Treynor, J., & Mazuy, K. (1966). Can mutual funds outguess the market. *Harvard business review, 44*(4), 131-136.
Treynor, J. L. (1961). Market value, time, and risk. *Time, and Risk (August 8, 1961)*.
Treynor, J. L., & Black, F. (1973). How to use security analysis to improve portfolio selection. *The Journal of business, 46*(1), 66-86.
Van Duuren, E., Plantinga, A., & Scholtens, B. (2016). ESG integration and the investment management process: Fundamental investing reinvented. *Journal of business ethics, 138*(3), 525-533.
Veith, S., Werner, J. R., & Zimmermann, J. (2009). Capital market response to emission rights returns: Evidence from the European power sector. *Energy economics, 31*(4), 605-613.
Verheyden, T., Eccles, R. G., & Feiner, A. (2016). ESG for all? The impact of ESG screening on return, risk, and diversification. *Journal of Applied Corporate Finance, 28*(2), 47-55.
Verma, M., & Hirpara, M. J. R. (2016). Performance evaluation of portfolio using the Sharpe, Jensen, and Treynor methods. *Scholars Journal of Economics, Business and Management, 3*(7), 382-390.
Von Wallis, M., & Klein, C. (2015). Ethical requirement and financial interest: a literature review on socially responsible investing. *Business Research, 8*(1), 61-98.
Wang, Q., Luo, J., Zhong, Z., & Borgna, A. (2011). CO2 capture by solid adsorbents and their applications: current status and new trends. *Energy & Environmental Science, 4*(1), 42-55.
Xia, L., Hao, W., Qin, J., Ji, F., & Yue, X. (2018). Carbon emission reduction and promotion policies considering social preferences and consumers' low-carbon awareness in the cap-and-trade system. *Journal of Cleaner Production, 195*, 1105-1124.
Zhou, B., Zhang, C., Song, H., & Wang, Q. (2019). How does emission trading reduce China's carbon intensity? An exploration using a decomposition and difference-in-differences approach. *Science of the total environment, 676*, 514-523.

Appendix

The appendix provides additional information on the benchmark, BIC and WIC portfolios. The tables provide information on the number of stocks per sector and the weights of the sector in the total portfolio. Moreover, information on whether the carbon intensity of stocks are reported or estimated by Sustainalytics per sector is provided. Besides, data of the country allocation within the investment portfolios and the weight of a country within the whole investment portfolio is given.

Sector allocation of benchmark portfolio 2016

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	209	13.12%
Consumer Staples	99	9.98%
Energy	69	5.72%
Financials	205	18.14%
Healthcare	100	13.58%
Industrials	227	11.12%
Information Technology	133	14.63%
Materials	106	3.70%
Real Estate	79	3.10%
Telecommunications	30	3.54%
Utilities	69	3.35%
Total	1326	100%

Percentage reported and estimated per sector of benchmark portfolio 2016

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	111	14.70%	98	17.16%
Consumer Staples	72	9.54%	27	4.73%
Energy	37	4.90%	32	5.60%
Financials	123	16.29%	82	14.36%
Healthcare	51	6.75%	49	8.58%
Industrials	132	17.48%	95	16.64%
Information Technology	67	8.87%	66	11.56%
Materials	72	9.54%	34	5.95%
Real Estate	25	3.31%	54	9.46%
Telecommunications	22	2.91%	8	1.40%
Utilities	43	5.70%	26	4.55%

Total	755	100%	571	100%

Country allocation of benchmark portfolio 2016

Country	# Stocks	Weight in portfolio
Australia	58	2.80%
Austria	5	0.08%
Belgium	8	0.23%
Bermuda	7	0.16%
Canada	73	3.03%
Channel Islands	1	0.01%
China	1	0.01%
Denmark	12	0.83%
Finland	10	0.31%
France	61	3.90%
Germany	45	3.88%
Hong Kong	36	1.32%
Ireland	12	1.17%
Israel	9	0.09%
Italy	12	0.72%
Japan	292	10.10%
Luxembourg	3	0.07%
Macau	3	0.04%
Mexico	1	0.01%
Netherlands	18	1.24%
New Zealand	7	0.07%
Norway	6	0.14%
Papua New Guinea	1	0.02%
Portugal	3	0.06%
Singapore	23	0.53%
Spain	18	1.22%
Sweden	22	0.98%
Switzerland	35	4.02%
United Kingdom	82	6.67%
United States	462	56.29%
Total	1326	100%

Sector allocation of best-in-class portfolio of 2016

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	42	13.12%
Consumer Staples	20	9.98%
Energy	14	5.72%
Financials	41	18.14%
Healthcare	20	13.58%
Industrials	45	11.12%
Information Technology	27	14.63%
Materials	21	3.70%
Real Estate	16	3.10%
Telecommunications	6	3.54%
Utilities	14	3.35%
Total	266	100.00%

Percentage reported and estimated per sector of best-in-class portfolio 2016

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	32	16.16%	10	14.71%
Consumer Staples	19	9.60%	1	1.47%
Energy	7	3.54%	7	10.29%
Financials	30	15.15%	11	16.18%
Healthcare	10	5.05%	10	14.71%
Industrials	36	18.18%	9	13.24%
Information Technology	16	8.08%	11	16.18%
Materials	16	8.08%	5	7.35%
Real Estate	12	6.06%	4	5.88%
Telecommunications	6	3.03%	0	0.00%
Utilities	14	7.07%	0	0.00%
Total	198	100.00%	68	100.00%

Country allocation of best-in-class portfolio of 2016

Country	# Stocks	Weight in portfolio
Australia	6	0.77%
Austria	0	0.00%
Belgium	3	0.61%
Bermuda	3	0.46%
Canada	15	1.85%
Channel Islands	1	0.05%
China	0	0.00%
Denmark	5	2.71%
Finland	3	1.01%
France	23	8.49%
Germany	12	5.63%
Hong Kong	0	0.00%
Ireland	3	2.98%
Israel	2	0.07%
Italy	4	1.69%
Japan	36	5.41%
Luxembourg	3	0.38%
Macau	0	0.00%
Mexico	0	0.00%
Netherlands	9	3.03%
New Zealand	4	0.45%
Norway	2	0.14%
Papua New Guinea	0	0.00%
Portugal	1	0.08%
Singapore	2	0.13%
Spain	2	0.18%
Sweden	6	1.14%
Switzerland	11	4.16%
United Kingdom	24	9.88%
United States	86	48.70%
Total	266	100.00%

Sector allocation of worst-in-class portfolio 2016

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	42	13.12%
Consumer Staples	20	9.98%
Energy	14	5.72%
Financials	41	18.14%
Healthcare	20	13.58%
Industrials	45	11.12%
Information Technology	27	14.63%
Materials	21	3.70%
Real Estate	16	3.10%
Telecommunications	6	3.54%
Utilities	14	3.35%
Total	266	100.00%

Percentage reported and estimated per sector of worst-in-class portfolio 2016

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	28	20.44%	14	10.85%
Consumer Staples	9	6.57%	11	8.53%
Energy	7	5.11%	7	5.43%
Financials	17	12.41%	24	18.60%
Healthcare	10	7.30%	10	7.75%
Industrials	24	17.52%	21	16.28%
Information Technology	15	10.95%	12	9.30%
Materials	10	7.30%	11	8.53%
Real Estate	3	2.19%	13	10.08%
Telecommunications	3	2.19%	3	2.33%
Utilities	11	8.03%	3	2.33%
Total	137	100.00%	129	100.00%

Country allocation of worst-in-class portfolio 2016

Country	# Stocks	Weight in Portfolio
Australia	16	2.59%
Austria	2	0.25%
Belgium	1	0.14%
Bermuda	0	0.00%
Canada	12	3.86%
Channel Islands	0	0.00%
China	0	0.00%
Denmark	2	0.40%
Finland	2	0.23%
France	7	1.98%
Germany	7	4.18%
Hong Kong	16	2.58%
Ireland	3	0.53%
Israel	3	0.18%
Italy	1	0.11%
Japan	68	11.03%
Luxembourg	0	0.00%
Macau	0	0.00%
Mexico	0	0.00%
Netherlands	0	0.00%
New Zealand	1	0.05%
Norway	2	0.26%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	5	0.36%
Spain	0	0.00%
Sweden	0	0.00%
Switzerland	7	2.38%
United Kingdom	10	5.01%
United States	101	63.89%
Total	266	100.00%

Sector allocation of benchmark portfolio 2017

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	217	12.39%
Consumer Staples	108	9.66%
Energy	67	6.70%
Financials	212	18.57%
Healthcare	112	11.98%
Industrials	239	11.69%
Information Technology	132	14.91%
Materials	109	4.37%
Real Estate	83	3.00%
Telecommunications	31	3.40%
Utilities	73	3.33%
Total	1383	100.00%

Percentage reported and estimated per sector of benchmark portfolio 2017

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	113	13.99%	104	18.09%
Consumer Staples	81	10.02%	27	4.70%
Energy	35	4.33%	32	5.57%
Financials	126	15.59%	86	14.96%
Healthcare	63	7.80%	49	8.52%
Industrials	143	17.70%	96	16.70%
Information Technology	73	9.03%	59	10.26%
Materials	78	9.65%	31	5.39%
Real Estate	27	3.34%	56	9.74%
Telecommunications	23	2.85%	8	1.39%
Utilities	46	5.69%	27	4.70%
Total	808	100.00%	575	100.00%

Country allocation of benchmark portfolio 2017

Country	# Stocks	Weight in Portfolio
Australia	58	2.79%
Austria	5	0.08%
Belgium	9	0.47%
Bermuda	8	0.22%
Canada	73	3.64%
Channel Islands	0	0.00%
China	1	0.00%
Denmark	15	0.66%
Finland	10	0.30%
France	65	3.84%
Germany	45	3.52%
Hong Kong	37	1.20%
Ireland	15	1.11%
Israel	11	0.25%
Italy	15	0.66%
Japan	295	9.56%
Luxembourg	4	0.08%
Macau	3	0.05%
Mexico	1	0.01%
Netherlands	18	1.41%
New Zealand	7	0.07%
Norway	7	0.15%
Papua New Guinea	1	0.02%
Portugal	3	0.06%
Singapore	24	0.51%
South Africa	1	0.01%
Spain	20	1.17%
Sweden	24	0.89%
Switzerland	34	3.67%
United Kingdom	87	5.96%
United States	487	57.61%
Total	1383	100.00%

Sector allocation of best-in-class portfolio 2017

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	43	12.39%
Consumer Staples	22	9.66%
Energy	13	6.70%
Financials	42	18.57%
Healthcare	22	11.98%
Industrials	48	11.69%
Information Technology	26	14.91%
Materials	22	4.37%
Real Estate	17	3.00%
Telecommunications	6	3.40%
Utilities	15	3.33%
Total	276	100.00%

Percentage reported and estimated per sector of best-in-class portfolio 2017

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	33	15.64%	10	15.38%
Consumer Staples	16	7.58%	6	9.23%
Energy	5	2.37%	8	12.31%
Financials	32	15.17%	10	15.38%
Healthcare	13	6.16%	9	13.85%
Industrials	39	18.48%	9	13.85%
Information Technology	18	8.53%	8	12.31%
Materials	19	9.00%	3	4.62%
Real Estate	15	7.11%	2	3.08%
Telecommunications	6	2.84%	0	0.00%
Utilities	15	7.11%	0	0.00%
Total	211	100.00%	65	100.00%

Country allocation of best-in-class portfolio 2017

Country	# Stocks	Weight in Portfolio
Australia	4	0.61%
Austria	0	0.00%
Belgium	4	0.71%
Bermuda	3	0.54%
Canada	14	2.80%
Channel Islands	0	0.00%
China	0	0.00%
Denmark	5	1.89%
Finland	2	0.82%
France	20	8.18%
Germany	8	3.58%
Hong Kong	2	0.35%
Ireland	4	1.38%
Israel	1	0.11%
Italy	3	1.16%
Japan	41	5.83%
Luxembourg	3	0.44%
Macau	0	0.00%
Mexico	0	0.00%
Netherlands	8	2.66%
New Zealand	3	0.41%
Norway	2	0.12%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	2	0.17%
South Africa	0	0.00%
Spain	2	0.31%
Sweden	7	1.10%
Switzerland	12	4.22%
United Kingdom	29	7.96%
United States	97	54.66%
Total	276	100.00%

Sector allocation of worst-in-class portfolio 2017

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	43	12.39%
Consumer Staples	22	9.66%
Energy	13	6.70%
Financials	42	18.57%
Healthcare	22	11.98%
Industrials	48	11.69%
Information Technology	26	14.91%
Materials	22	4.37%
Real Estate	17	3.00%
Telecommunications	6	3.40%
Utilities	15	3.33%
Total	276	100.00%

Percentage reported and estimated per sector of worst-in-class portfolio 2017

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	24	16.11%	19	14.96%
Consumer Staples	14	9.40%	8	6.30%
Energy	8	5.37%	5	3.94%
Financials	16	10.74%	26	20.47%
Healthcare	15	10.07%	7	5.51%
Industrials	27	18.12%	21	16.54%
Information Technology	19	12.75%	7	5.51%
Materials	10	6.71%	12	9.45%
Real Estate	3	2.01%	14	11.02%
Telecommunications	2	1.34%	4	3.15%
Utilities	11	7.38%	4	3.15%
Total	149	100.00%	127	100.00%

Country allocation of worst-in-class portfolio 2017

Country	# Stocks	Weight in Portfolio
Australia	18	4.58%
Austria	2	0.34%
Belgium	3	2.83%
Bermuda	0	0.00%
Canada	14	5.91%
Channel Islands	0	0.00%
China	0	0.00%
Denmark	3	0.68%
Finland	2	0.22%
France	6	2.49%
Germany	8	3.58%
Hong Kong	16	2.19%
Ireland	4	0.71%
Israel	2	0.85%
Italy	0	0.00%
Japan	65	10.56%
Luxembourg	1	0.11%
Macau	3	0.33%
Mexico	0	0.00%
Netherlands	1	0.83%
New Zealand	1	0.05%
Norway	3	0.97%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	5	0.32%
South Africa	1	0.08%
Spain	3	1.56%
Sweden	3	0.43%
Switzerland	5	1.14%
United Kingdom	10	5.77%
United States	97	53.48%
Total	276	100.00%

Sector allocation of benchmark portfolio 2018

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	217	12.38%
Consumer Staples	108	9.07%
Energy	65	5.87%
Financials	224	18.45%
Healthcare	117	11.72%
Industrials	252	11.99%
Information Technology	149	17.04%
Materials	116	4.69%
Real Estate	88	2.84%
Telecommunications	31	2.83%
Utilities	73	3.12%
Total	1440	100.00%

Percentage reported and estimated per sector of benchmark portfolio 2018

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	130	13.79%	87	17.51%
Consumer Staples	84	8.91%	24	4.83%
Energy	37	3.92%	28	5.63%
Financials	146	15.48%	78	15.69%
Healthcare	73	7.74%	44	8.85%
Industrials	176	18.66%	76	15.29%
Information Technology	82	8.70%	67	13.48%
Materials	90	9.54%	26	5.23%
Real Estate	46	4.88%	42	8.45%
Telecommunications	26	2.76%	5	1.01%
Utilities	53	5.62%	20	4.02%
Total	943	100.00%	497	100.00%

Country allocation of benchmark portfolio 2018

Country	# Stocks	Weight in portfolio
Argentina	1	0.04%
Australia	60	2.75%
Austria	5	0.11%
Belgium	10	0.46%
Bermuda	8	0.18%
Canada	74	3.57%
Channel Islands	0	0.00%
China	2	0.02%
Denmark	16	0.74%
Finland	10	0.31%
France	69	3.68%
Germany	53	3.83%
Hong Kong	35	1.21%
Ireland	19	1.26%
Israel	10	0.19%
Italy	17	0.80%
Japan	302	9.64%
Luxembourg	5	0.12%
Macau	3	0.06%
Mexico	1	0.01%
Netherlands	19	1.57%
New Zealand	7	0.07%
Norway	6	0.15%
Papua New Guinea	1	0.02%
Portugal	3	0.06%
Singapore	24	0.54%
South Africa	0	0.00%
Spain	20	1.21%
Sweden	24	0.82%
Switzerland	36	3.68%
United Kingdom	89	6.11%
United States	511	56.80%
Total	1439	100.00%

Sector allocation of best-in-class portfolio 2018

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	43	12.38%
Consumer Staples	22	9.07%
Energy	13	5.87%
Financials	45	18.45%
Healthcare	23	11.72%
Industrials	50	11.99%
Information Technology	30	17.04%
Materials	23	4.69%
Real Estate	18	2.84%
Telecommunications	6	2.83%
Utilities	15	3.12%
Total	288	100.00%

Percentage reported and estimated per sector of best-in-class portfolio 2018

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	36	14.46%	7	17.95%
Consumer Staples	18	7.23%	4	10.26%
Energy	8	3.21%	5	12.82%
Financials	36	14.46%	9	23.08%
Healthcare	17	6.83%	6	15.38%
Industrials	47	18.88%	3	7.69%
Information Technology	26	10.44%	4	10.26%
Materials	22	8.84%	1	2.56%
Real Estate	18	7.23%	0	0.00%
Telecommunications	6	2.41%	0	0.00%
Utilities	15	6.02%	0	0.00%
Total	249	100.00%	39	100.00%

Country allocation of best-in-class portfolio 2018

Country	# Stocks	Weight in portfolio
Argentina	1	0.11%
Australia	5	0.66%
Austria	0	0.00%
Belgium	1	0.14%
Bermuda	3	0.38%
Canada	18	2.95%
Channel Islands	0	0.00%
China	0	0.00%
Denmark	7	2.73%
Finland	2	0.77%
France	22	6.80%
Germany	12	3.24%
Hong Kong	6	2.82%
Ireland	3	1.23%
Israel	0	0.00%
Italy	3	0.74%
Japan	46	8.37%
Luxembourg	2	0.17%
Macau	0	0.00%
Mexico	0	0.00%
Netherlands	8	2.87%
New Zealand	3	0.22%
Norway	1	0.08%
Papua New Guinea	0	0.00%
Portugal	1	0.18%
Singapore	1	0.06%
South Africa	0	0.00%
Spain	2	0.32%
Sweden	7	1.02%
Switzerland	11	3.52%
United Kingdom	28	7.21%
United States	95	53.42%
Total	288	100.00%

Sector allocation of worst-in-class portfolio 2018

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	43	12.38%
Consumer Staples	22	9.07%
Energy	13	5.87%
Financials	45	18.45%
Healthcare	23	11.72%
Industrials	50	11.99%
Information Technology	30	17.04%
Materials	23	4.69%
Real Estate	18	2.84%
Telecommunications	6	2.83%
Utilities	15	3.12%
Total	288	100.00%

Percentage reported and estimated per sector of worst-in-class portfolio 2018

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	27	17.09%	16	12.31%
Consumer Staples	14	8.86%	8	6.15%
Energy	9	5.70%	4	3.08%
Financials	15	9.49%	30	23.08%
Healthcare	12	7.59%	11	8.46%
Industrials	29	18.35%	21	16.15%
Information Technology	16	10.13%	14	10.77%
Materials	13	8.23%	10	7.69%
Real Estate	9	5.70%	9	6.92%
Telecommunications	3	1.90%	3	2.31%
Utilities	11	6.96%	4	3.08%
Total	158	100.00%	130	100.00%

Country allocation of worst-in-class portfolio 2018

Country	# Stocks	Weight in portfolio
Argentina	0	0.00%
Australia	19	3.79%
Austria	1	0.10%
Belgium	2	1.63%
Bermuda	1	0.19%
Canada	15	5.41%
Channel Islands	0	0.00%
China	1	0.08%
Denmark	3	0.66%
Finland	1	0.13%
France	6	2.69%
Germany	12	5.54%
Hong Kong	11	1.64%
Ireland	4	0.79%
Israel	2	0.12%
Italy	2	0.96%
Japan	66	9.23%
Luxembourg	2	0.48%
Macau	2	0.33%
Mexico	0	0.00%
Netherlands	4	0.55%
New Zealand	1	0.07%
Norway	3	1.07%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	7	0.47%
South Africa	0	0.00%
Spain	3	1.59%
Sweden	3	0.64%
Switzerland	4	1.32%
United Kingdom	8	3.85%
United States	105	56.64%
Total	288	100.00%

Sector allocation of benchmark portfolio 2019

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	218	12.76%
Consumer Staples	113	8.66%
Energy	64	5.38%
Financials	220	16.79%
Healthcare	123	13.26%
Industrials	257	11.15%
Information Technology	155	18.36%
Materials	119	4.22%
Real Estate	90	3.05%
Telecommunications	32	2.85%
Utilities	75	3.51%
Total	1466	100.00%

Percentage reported and estimated per sector of benchmark portfolio 2019

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	113	13.36%	105	16.94%
Consumer Staples	72	8.51%	41	6.61%
Energy	38	4.49%	26	4.19%
Financials	122	14.42%	98	15.81%
Healthcare	62	7.33%	61	9.84%
Industrials	166	19.62%	91	14.68%
Information Technology	69	8.16%	86	13.87%
Materials	82	9.69%	37	5.97%
Real Estate	42	4.96%	48	7.74%
Telecommunications	24	2.84%	8	1.29%
Utilities	56	6.62%	19	3.06%
Total	846	100.00%	620	100.00%

Country allocation of benchmark portfolio 2019

Country	# Stocks	Weight in portfolio
Argentina	1	0.04%
Australia	64	2.58%
Austria	6	0.09%
Belgium	10	0.36%
Bermuda	6	0.15%
Canada	78	3.44%
Channel Islands	0	0.00%
China	2	0.01%
Denmark	16	0.66%
Finland	10	0.29%
France	70	3.48%
Germany	54	3.17%
Hong Kong	36	1.28%
Ireland	22	1.35%
Israel	10	0.16%
Italy	18	0.75%
Japan	302	9.01%
Luxembourg	7	0.13%
Macau	3	0.05%
Mexico	1	0.01%
Netherlands	19	1.50%
New Zealand	7	0.09%
Norway	7	0.22%
Papua New Guinea	0	0.00%
Portugal	3	0.06%
Singapore	23	0.51%
South Africa	0	0.00%
Spain	19	1.07%
Sweden	28	0.92%
Switzerland	38	3.61%
United Kingdom	87	5.38%
United States	519	59.63%
Total	1466	100.00%

Sector allocation of best-in-class portfolio 2019

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	44	12.76%
Consumer Staples	23	8.66%
Energy	13	5.38%
Financials	44	16.79%
Healthcare	25	13.26%
Industrials	51	11.15%
Information Technology	31	18.36%
Materials	24	4.22%
Real Estate	18	3.05%
Telecommunications	6	2.85%
Utilities	15	3.51%
Total	294	100.00%

Percentage reported and estimated per sector of best-in-class portfolio 2019

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	34	13.99%	10	19.61%
Consumer Staples	20	8.23%	3	5.88%
Energy	9	3.70%	4	7.84%
Financials	32	13.17%	12	23.53%
Healthcare	17	7.00%	8	15.69%
Industrials	45	18.52%	6	11.76%
Information Technology	24	9.88%	7	13.73%
Materials	23	9.47%	1	1.96%
Real Estate	18	7.41%	0	0.00%
Telecommunications	6	2.47%	0	0.00%
Utilities	15	6.17%	0	0.00%
Total	243	100.00%	51	100.00%

Country allocation of best-in-class portfolio 2019

Country	# Stocks	Weight in portfolio
Argentina	1	0.12%
Australia	7	0.88%
Austria	0	0.00%
Belgium	3	0.43%
Bermuda	3	0.51%
Canada	12	2.13%
Channel Islands	0	0.00%
China	0	0.00%
Denmark	6	0.91%
Finland	3	1.03%
France	24	7.21%
Germany	16	5.02%
Hong Kong	4	2.98%
Ireland	5	3.39%
Israel	0	0.00%
Italy	3	0.72%
Japan	38	5.04%
Luxembourg	3	0.27%
Macau	0	0.00%
Mexico	0	0.00%
Netherlands	8	3.07%
New Zealand	3	0.35%
Norway	1	0.08%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	1	0.07%
South Africa	0	0.00%
Spain	5	0.71%
Sweden	13	2.85%
Switzerland	17	6.92%
United Kingdom	36	9.82%
United States	82	45.48%
Total	294	100.00%

Sector allocation of worst-in-class portfolio 2019

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	44	12.76%
Consumer Staples	23	8.66%
Energy	13	5.38%
Financials	44	16.79%
Healthcare	25	13.26%
Industrials	51	11.15%
Information Technology	31	18.36%
Materials	24	4.22%
Real Estate	18	3.05%
Telecommunications	6	2.85%
Utilities	15	3.51%
Total	294	100.00%

Percentage reported and estimated per sector of worst-in-class portfolio 2019

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	22	16.18%	22	13.92%
Consumer Staples	11	8.09%	12	7.59%
Energy	8	5.88%	5	3.16%
Financials	8	5.88%	36	22.78%
Healthcare	14	10.29%	11	6.96%
Industrials	28	20.59%	23	14.56%
Information Technology	13	9.56%	18	11.39%
Materials	10	7.35%	14	8.86%
Real Estate	4	2.94%	14	8.86%
Telecommunications	4	2.94%	2	1.27%
Utilities	14	10.29%	1	0.63%
Total	136	100.00%	158	100.00%

Country allocation of worst-in-class portfolio 2019

Country	# Stocks	Weight in Portfolio
Argentina	0	0.00%
Australia	17	4.39%
Austria	1	0.06%
Belgium	2	1.44%
Bermuda	1	0.24%
Canada	19	6.43%
Channel Islands	0	0.00%
China	1	0.07%
Denmark	2	0.38%
Finland	3	0.33%
France	7	2.09%
Germany	12	4.32%
Hong Kong	15	2.82%
Ireland	6	1.19%
Israel	1	0.09%
Italy	1	0.07%
Japan	78	10.29%
Luxembourg	2	0.34%
Macau	2	0.40%
Mexico	0	0.00%
Netherlands	2	0.30%
New Zealand	1	0.07%
Norway	2	1.14%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	6	0.35%
South Africa	0	0.00%
Spain	1	0.18%
Sweden	6	1.59%
Switzerland	3	1.03%
United Kingdom	6	3.10%
United States	97	57.30%
Total	294	100.00%

Sector allocation of benchmark portfolio 2020

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	221	12.76%
Consumer Staples	113	8.02%
Energy	58	4.49%
Financials	227	16.07%
Healthcare	135	12.95%
Industrials	254	10.82%
Information Technology	185	21.15%
Materials	122	4.64%
Real Estate	97	3.17%
Telecommunications	32	2.57%
Utilities	76	3.34%
Total	1520	100.00%

Percentage reported and estimated per sector of benchmark portfolio 2020

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	127	13.86%	94	15.56%
Consumer Staples	78	8.52%	35	5.79%
Energy	41	4.48%	17	2.81%
Financials	134	14.63%	93	15.40%
Healthcare	61	6.66%	74	12.25%
Industrials	161	17.58%	93	15.40%
Information Technology	83	9.06%	102	16.89%
Materials	90	9.83%	32	5.30%
Real Estate	53	5.79%	44	7.28%
Telecommunications	27	2.95%	5	0.83%
Utilities	61	6.66%	15	2.48%
Total	916	100.00%	604	100.00%

Country allocation of benchmark portfolio 2020

Country	# Stocks	Weight in portfolio
Argentina	1	0.06%
Australia	66	2.38%
Austria	6	0.08%
Belgium	11	0.35%
Bermuda	6	0.16%
Canada	83	3.56%
Channel Islands	0	0.00%
China	1	0.00%
Denmark	16	0.64%
Finland	11	0.34%
France	68	3.33%
Germany	52	2.93%
Hong Kong	35	1.08%
Ireland	21	1.43%
Israel	11	0.17%
Italy	19	0.73%
Japan	305	8.31%
Luxembourg	6	0.10%
Macau	2	0.04%
Mexico	0	0.00%
Netherlands	22	1.63%
New Zealand	8	0.10%
Norway	7	0.16%
Papua New Guinea	0	0.00%
Portugal	3	0.06%
Singapore	24	0.46%
South Africa	0	0.00%
Spain	20	0.92%
Sweden	26	0.81%
Switzerland	38	3.52%
United Kingdom	94	5.42%
United States	558	61.24%
Total	1520	100.00%

Sector allocation of best-in-class portfolio 2020

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	44	12.76%
Consumer Staples	23	8.02%
Energy	12	4.49%
Financials	45	16.07%
Healthcare	27	12.95%
Industrials	51	10.82%
Information Technology	37	21.15%
Materials	24	4.64%
Real Estate	19	3.17%
Telecommunications	6	2.57%
Utilities	15	3.34%
Total	303	100.00%

Percentage reported and estimated per sector of best-in-class portfolio 2020

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	27	12.27%	17	20.48%
Consumer Staples	19	8.64%	4	4.82%
Energy	6	2.73%	6	7.23%
Financials	30	13.64%	15	18.07%
Healthcare	15	6.82%	12	14.46%
Industrials	45	20.45%	6	7.23%
Information Technology	24	10.91%	13	15.66%
Materials	19	8.64%	5	6.02%
Real Estate	16	7.27%	3	3.61%
Telecommunications	6	2.73%	0	0.00%
Utilities	13	5.91%	2	2.41%
Total	220	100.00%	83	100.00%

Country allocation of best-in-class portfolio 2020

Country	# Stocks	Weight in portfolio
Argentina	1	0.19%
Australia	8	0.71%
Austria	0	0.00%
Belgium	3	0.39%
Bermuda	3	0.53%
Canada	12	2.72%
Channel Islands	0	0.00%
China	0	0.00%
Denmark	5	0.58%
Finland	3	1.14%
France	24	7.01%
Germany	14	3.85%
Hong Kong	2	2.80%
Ireland	4	3.48%
Israel	1	0.10%
Italy	4	0.77%
Japan	41	3.91%
Luxembourg	2	0.23%
Macau	0	0.00%
Mexico	0	0.00%
Netherlands	10	4.06%
New Zealand	3	0.35%
Norway	0	0.00%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	3	0.18%
South Africa	0	0.00%
Spain	4	0.50%
Sweden	10	1.51%
Switzerland	15	3.30%
United Kingdom	28	4.97%
United States	103	56.70%
Total	303	100.00%

Sector allocation of worst-in-class portfolio 2020

Sector	# Stocks	Weight in portfolio
Consumer Discretionary	44	12.76%
Consumer Staples	23	8.02%
Energy	12	4.49%
Financials	45	16.07%
Healthcare	27	12.95%
Industrials	51	10.82%
Information Technology	37	21.15%
Materials	24	4.64%
Real Estate	19	3.17%
Telecommunications	6	2.57%
Utilities	15	3.34%
Total	303	100.00%

Percentage reported and estimated per sector of worst-in-class portfolio 2020

Sector	# Reported	% Reported	# Estimated	% Estimated
Consumer Discretionary	31	17.42%	13	10.40%
Consumer Staples	13	7.30%	10	8.00%
Energy	10	5.62%	2	1.60%
Financials	17	9.55%	28	22.40%
Healthcare	13	7.30%	14	11.20%
Industrials	28	15.73%	23	18.40%
Information Technology	18	10.11%	19	15.20%
Materials	18	10.11%	6	4.80%
Real Estate	9	5.06%	10	8.00%
Telecommunications	6	3.37%	0	0.00%
Utilities	15	8.43%	0	0.00%
Total	178	100.00%	125	100.00%

Country allocation of worst-in-class portfolio 2020

Country	# Stocks	Weight in portfolio
Argentina	0	0.00%
Australia	17	2.85%
Austria	0	0.00%
Belgium	2	1.57%
Bermuda	1	0.30%
Canada	16	5.56%
Channel Islands	0	0.00%
China	0	0.00%
Denmark	3	0.88%
Finland	2	0.17%
France	6	2.21%
Germany	13	3.78%
Hong Kong	15	1.85%
Ireland	3	0.89%
Israel	2	0.24%
Italy	1	0.06%
Japan	83	11.83%
Luxembourg	3	0.35%
Macau	2	0.44%
Mexico	0	0.00%
Netherlands	3	0.73%
New Zealand	1	0.07%
Norway	2	0.66%
Papua New Guinea	0	0.00%
Portugal	0	0.00%
Singapore	7	0.85%
South Africa	0	0.00%
Spain	3	1.25%
Sweden	4	1.23%
Switzerland	5	1.82%
United Kingdom	10	4.51%
United States	99	55.93%
Total	303	100.00%