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Financial Engineering and Management

A Framework for Evaluating Market Risks in Equity Portfolios Linked to Biodiversity Decline

Author:
Ferial El Bou Messaoudi

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Prof. dr. Laura Spierdijk	University Twente
Prof. dr. Dirk Broeders	De Nederlandsche Bank
Daniel Dimitrov	De Nederlandsche Bank
Vincent Streichert	De Nederlandsche Bank

Abstract

In partnership with De Nederlandsche Bank, this study aims to investigate the market risks associated with biodiversity loss in equity portfolios. With rising sea levels, more wildfires, and warmer temperatures, the consequences of losing biodiversity become clearer. Cutting down forests, invasive species, and species dying out pose serious threats to both humans and animals. Biodiversity and its ecosystems are important for the economy since almost every economic activity depends on them.

Biodiversity and its ecosystems play a crucial role in supporting various sectors of the economy, making it essential to understand and quantify the implications of biodiversity loss for financial markets. There is a lack of methods in the existing literature to identify the physical and transition risks linked to biodiversity loss and understand how they affect market risk.

This study presents a framework for identifying biodiversity risk exposure within an equity portfolio. We follow the traditional Fama-French approach with an extension of biodiversity risk factors. Using the High-Minus-Low portfolio construction method, aligned with the Fama-French approach. This approach constructs the physical and transition biodiversity risk factors, indicating a positive risk premium associated with biodiversity transition risk. Moreover, the framework aims to assess the market risk linked to biodiversity risk. Through biodiversity time series regression, the sensitivity of a globally diversified equity portfolio to biodiversity risk factors is estimated, revealing minimal sensitivity. Lastly, potential losses of the equity portfolio, including biodiversity risk, are estimated. The sensitivity analysis indicates a small impact of biodiversity risk factors on market risk within the equity portfolio. This research creates a framework to incorporate biodiversity risk into existing market risk models.

Keywords: Market Risk, Physical Risk, Transition Risk, Time Series Regression, Fama-French Model, Biodiversity Betas, Biodiversity Risk Factors, Value at Risk, Expected Shortfall, High-Minus-Low Portfolio

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Abbreviations

ACWI All Country World Index

BIA Biodiversity Impact Analytics

BIAT Biodiversity Impact Assessment Tool

CAPM Capital Asset Pricing Model

CBF Corporate Biodiversity Footprint

DNB De Nederlandsche Bank

ECB European Central Bank

ENCORE Exploring Natural Capital Opportunities, Risks, and Exposure

ES Expected Shortfall

ESG Environmental, Social, and Governance

GBS Global Biodiversity Score

GDP Gross domestic product

GICS Global Industry Classification Standard

GLOBIO Global Biodiversity model for policy support

HML High Minus Low

IBAT Integrated Biodiversity Assessment Tool

INSPIRE International Network for Sustainable financial Policy Insights, Research and Exchange

ISIN International Securities Identification Number

ISS Institutional Shareholder Services

MSA Mean Species Abundance

MSCI Morgan Stanley Capital International

NGFS Network for Greening the Financial System

OLS Ordinary Least Squares

PDF Potentially Disappeared Fraction

PHY High Physical - Minus - Low Physical

RMRF Excess return on the market portfolio

SMB Small Minus Big

STAR Species Threat Abatement and Restoration

TNFD Taskforce on Nature-related Financial Disclosures

TRA High Transition - Minus - Low Transition

UMD Momentum

VaR Value at Risk

WWF-BRF World Wide Fund - Biodiversity Risk Filter

Chapter 1

Introduction

> *"It seems to me that the natural world is the greatest source of excitement; the greatest source of visual beauty; the greatest source of intellectual interest. It is the greatest source of so much in life that makes life worth living." - David Attenborough*

The world around us is changing. Rising sea levels, escalating wildfire occurrences, increasing temperature, and loss of biodiversity. Consequently, recent years have witnessed a heightened focus on environmental preservation and sustainability goals. Aligned with the United Nations' sustainable development goals, highlighted by Mohieldin and Caballero (2015), the essential is to *"Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation, and halt biodiversity loss."* In collaboration with De Nederlandsche Bank (DNB), this study aims to explore the market risks associated with biodiversity decline in equity portfolios. As a central bank, DNB is committed to ensuring price stability and sustainable prosperity. An important aspect of DNB's mandate is the management on their reserves with an emphasis on sustainability and its impacts including financial, environmental, social, and governance considerations.

1.1 Problem context

The concept of biodiversity includes various parts of the natural world. The definition used by the IPBES (2019), one of the leading platforms focused on biodiversity and ecosystems, entails diversity within species, among species, and within ecosystems. The climate is changing, and this change is also having an impact on biodiversity and ecosystems. As highlighted by Duraiappah et al. (2005), it is necessary to recognize that human well-being is massively affected by biodiversity and the services provided by the ecosystems.

Climate change and biodiversity loss share some important traits. Climate change affects plants and animal species, as well as environmental ecosystems. On the other hand, biodiversity loss can make climate change worse. To illustrate the severity of the issue, consider the deforestation happening last year in Brazil, the loss of forests was equal to the size of Switzerland, as reported by McGrath and Poynting (2023). The burning of these forests further intensifies the climate problems, releasing more CO_2 into the atmosphere. The lost forest can no longer absorb CO_2, resulting in a compounding effect that drives the temperatures upwards. These forests are critical to biodiversity, with both human populations and wildlife relying heavily on these ecosystems. Another consequence of human activities is the introduction of alien species to new regions. As documented by Roy et al. (2023), 60% of animal and plant extinctions are because of these non-native species. Due to globalization and increased transportation, the expansion of these alien species is expected to continue, expanding their impact on biodiversity. The consequences of deforestation, the spread of alien species, and the increasing rate of extinction of species have far-reaching implications for both human and animal life. Duraiappah et al. (2005) highlight how the loss of biodiversity and the damage to ecosystems have an impact on various aspects of human well-being. For instance, biodiversity plays a crucial role in the agricultural sector.

Nevertheless, nature demonstrates resilience. Despite the negative outlook presented, there are also positive stories, as highlighted in Alberts (2023). This discusses an island's remarkable transformation, rapidly recovering after the removal of invasive animals. This story shows nature's quick adaptability, which leads to the return of vegetation and the recolonization of wildlife on the island.

Biodiversity loss and financial risks

Biodiversity and its ecosystems have a significant influence on the economy, as nearly every economic process relies, in one way or another, on ecosystem services. Primary industries like agriculture and fisheries naturally depend on these services. However, it is essential to recognize that secondary and tertiary industries also have indirect dependencies on ecosystem services, as outlined by NGFS and INSPIRE (2021). Underlying the importance of biodiversity within the economic sector, Arnold (2023) emphasized that 'Destroy nature and you destroy the economy'. Boldrini et al. (2023) show the financial risks coming from the degradation of natural ecosystems. This analysis revealed that 72% of the companies in the Eurozone and 75% of the loans by the banks are exposed to the risk of biodiversity loss.

In accordance with Kedward et al. (2022), financial institutions are exposed through their investments, lending activities, and insurances to the impact of biodiversity loss. The risks of biodiversity loss when materialized can negatively impact the operations of businesses in the future, potentially leading to reduced profitability and an increased likelihood of default. Consequently, these risks can translate into an increased market risk for financial institutions. If these risks accumulate, they could potentially develop into systematic financial exposure, this requires the attention of central banks and other financial supervisors. The occurrence of such risks can be triggered by changes in biodiversity, either through abrupt shocks or long-term trends, as highlighted by the Network for Greening the Financial System (NGFS) and International Network for Sustainable financial Policy Insights, Research and Exchange (INSPIRE) in NGFS and INSPIRE (2022).

Biodiversity loss poses a threat to the economy. These risks associated with the services of the ecosystem are currently not priced appropriately in economic markets. Giglio et al. (2023) indicate that investors doubt if the current stock prices accurately reflect the biodiversity risks. A challenge is that the majority of companies and investors do not understand the risks and implications related to biodiversity loss. Consequently, they do not account for these considerations in their strategies and capital allocations. Biodiversity should no longer be only a corporate social responsibility but should be an element of the management of their risk, as outlined by Taskforce on Nature-related Financial Disclosures (TNFD) in the paper TNFD (2023),

However, assessing biodiversity-related risks is a difficult task, as emphasized by NGFS and INSPIRE (2021), given the complexity of ecosystems. Ecosystems are characterized by tipping points, feedback loops, and non-linear changes, introducing complexities that make it challenging to predict the potential risks accurately. Moreover, historical data is insufficient for forecasting as there are no scenarios to compare it with, as we do not know the impact of future biodiversity loss compared to events that already happened.

De Nederlandsche Bank

DNB is the central bank of the Netherlands, with the core mission of preserving financial stability within the country. This mandate is achieved through the maintenance of price stability, secure payments, and reliable financial institutions. Given the Netherlands' membership in the Eurozone, DNB is part of the Eurosystem, with the European Central Bank (ECB) responsible for the monetary policies. Besides that, DNB works closely with the other central banks within the Eurozone. Consequently, DNB's mission for financial stability extends beyond the borders of the Netherlands. This collective effort ensures macroeconomic improvement and price stability across Europe. In alignment with their corporate social responsibility, DNB (2023a) states that: *'We are committed to financial stability and contribute to sustainable prosperity in the Netherlands. We believe it is important that economic growth should not harm our living environment'*.

Central banks, including DNB, are recognized by NGFS (2019), as having a crucial role to play in addressing biodiversity-related risks. The loss of biodiversity can cause risks to financial institutions and consequently influence financial stability. Given that one of the main tasks of the central banks is to maintain financial stability, the NGFS encourages central banks to assess and take action on financial risks coming from biodiversity loss.

The risk management department of DNB is primarily responsible for the identification, assessment, mitigation, and monitoring of the risks associated with the balance sheet of DNB. This role extends to managing the risks related to monetary policies and their investments. Various risks are examined, including interest rate risks, asset-liquidity risks, credit risks, and market risks. DNB maintains its investments valued at 8.5 billion, and these investments comply with strict DNB-established criteria as stated by DNB (2023b). In evaluating their investments, DNB places strong value on sustainability, also considering biodiversity. Consequently, the risk management department has an interest in assessing the risks associated with the impact on biodiversity within their balance sheet.

1.2 Core problem

Biodiversity and its ecosystems are transforming, impacting the economy. Climate change is a key driver of this transformation, leading to biodiversity loss. The loss of biodiversity triggers various forces. The risks coming from biodiversity loss can be categorized into two risks by NGFS and INSPIRE (2021), as follows:

1. **Physical risks**
   These risks derive from potential disruptions to business operations or changes in customer demand due to biodiversity loss. An example of this is demonstrated in van Toor et al. (2020), which reveals the impact of biodiversity loss on the operations of industries. More specifically, 75% of important food crops depend, to some extent, on animal pollination. The reduction of animal pollination, thus biodiversity, shows a clear physical risk, affecting production systems and, consequently, the profitability of food processors.

2. **Transition risks**
   These risks derive from mitigation actions in response to biodiversity loss, resulting in economic loss. These mitigations could entail regulations, technological shifts, or changing consumer preferences. An example is the nitrogen crisis in the Netherlands, where the government aims to regulate the nitrogen emissions from the agriculture sector. These regulations have implications for farmers and the agriculture sector, potentially leading to a

reduction in the profitability and the number of farmers. Businesses with dependencies on the agricultural sector also face risks.

van Toor et al. (2020) introduce a third biodiversity risk, namely reputational risk, which involves the risk of financing companies where environmental controversies are discovered or provided inaccurate biodiversity data. Another biodiversity risk is liability risk, as described by OECD (2023), which entails the risk of failing to prevent biodiversity loss or actions that damage the ecosystem. However, most literature primarily discusses physical and transition risks as the main risks. Reputational and liability risks are often considered under transition risk. In this research, we focus solely on physical and transition risks. These risks are interconnected, as increased physical risk might cause the implementation of stricter government policies, causing transition risks. A lack of action in transitioning to restore biodiversity could raise the risk of physical shocks in the long term, as discussed by OECD (2023).

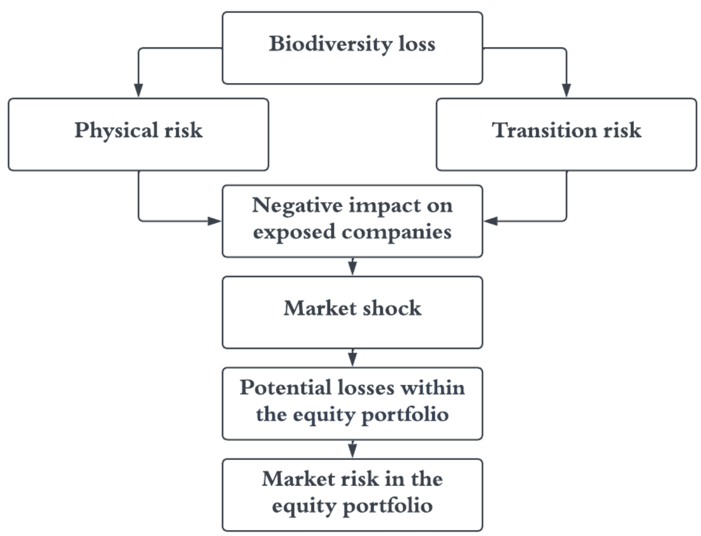


Figure 1.1: Problem cluster

The physical and transition risks arising from biodiversity loss have a negative effect on companies exposed to such risks. These companies may be dependent on specific ecosystems. In the event of a physical shock, there is a potential for a loss of profitability and an increase in default risks. Similarly, companies exposed to transition risks, which may impact ecosystems, could face regulations aimed at mitigating this impact. Consequently, regulatory changes or other transition shocks may lead to a loss of profitability and an increase in default risks for these companies. These risks pose a potential threat to companies, indicating possible shifts in profitability and default risks. These negative effects on companies, in turn, can influence the equity market. The physical and transition risks have the potential to impact equities, resulting in price fluctuations and potentially culminating in a market shock. Ultimately, biodiversity loss could trigger both physical and transition market shocks, be it through abrupt environmental changes or regulations. These shocks result in a negative impact on companies that either depend on or impact biodiversity. Consequently, biodiversity loss could lead to market risk.

An equity portfolio is affected by both physical and transition biodiversity risks. In the event of a market shock triggered by either physical drivers or regulations, the portfolio may be affected. Resulting from the fluctuating prices of its invested companies. This could lead to potential increased losses. Consequently, biodiversity loss has the potential to impact the market risk of a portfolio. Figure 1.1 shows the problem cluster that involves the forces and relationships of the impact of biodiversity loss on an equity portfolio, as recommended by Heerkens and Van Winden (2021).

Currently, there is a lack of methods in the existing body of literature for the identification of the physical and transition risks and assessing the market risk relating to biodiversity loss for central banks. As a response to this gap, DNB initiates research to develop an approach for identifying and assessing these risks. Not only for DNB to get insight, but also to help other financial institutions to understand how they can assess their market risks related to biodiversity loss. Resulting in the core problem for this research:

There is a lack of understanding regarding the exposure to risks associated with biodiversity loss, and how these risks impact the market risk of an equity portfolio.

Investigating the risks linked to biodiversity loss adds to the existing body of literature, providing financial institutions with a way to identify their exposure to both physical and transition risks in their investments. By understanding these risks, an evaluation of market risks associated with biodiversity loss can be conducted. This approach provides financial institutions with a method to assess the market risk coming from biodiversity loss, thereby contributing to the existing literature.

1.3 Research goal

In addressing the problem described in section 1.2, this research is conducted. To gain an understanding regarding the identification of the risks associated with biodiversity, an approach should be established focusing on both physical and transition risks. The second step is to assess the market risks arising from both biodiversity risks. For the assessment we also need to create an approach, we will focus on an equity portfolio. Resulting in the research question to tackle the core problem:

How can a framework be established to identify biodiversity risks and assess market risks in equity portfolios related to biodiversity loss?

Addressing this research question will lead to the identification of the vulnerabilities to biodiversity risk within an equity portfolio. Additionally, it will result in evaluating the market risk impact that biodiversity loss entails for a portfolio.

1.3.1 Research questions

To tackle the research question, three sub-questions are identified. The research is structured around these three sub-questions, each giving separate questions.

1. How can the risks associated with biodiversity loss be identified and assessed?
    (a) What are appropriate indicators for physical and transition risks related to biodiversity loss?
    (b) What methods are appropriate to use with regard to the assessment of market risks regarding biodiversity loss?
2. How can the market risk linked to biodiversity loss be identified and evaluated within the context of an equity portfolio?
    (a) How can market risk be analyzed concerning physical and transition biodiversity risks?
    (b) What is the extent and nature of the available data that can be used to assess physical and transition biodiversity risks?
3. What is the exposure of an equity portfolio to biodiversity loss, and how does it influence market risk within the portfolio?
    (a) How is an equity portfolio exposed to physical and transition risks associated with biodiversity?
    (b) What is the impact of the biodiversity risks on the market risk of an equity portfolio, and what are the implications of these risks?

1.3.2 Research design

This section explains the research design employed to address the research question, which centers on the identification of both physical and transition risks, along with an assessment of the market risk linked to biodiversity loss on an equity portfolio. Figure 1.2 illustrates the structure of the research.

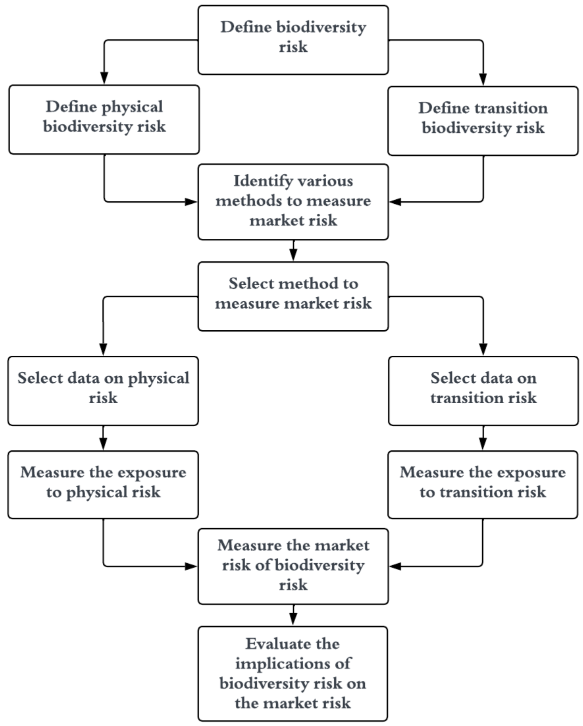


Figure 1.2: Research design

The first step is to define biodiversity risk through both physical and transition risks. This is done by a literature review of the current literature regarding the assessment of biodiversity-related risks, focusing on physical and transition risks. Through this literature review, possible indicators can be found. The second part of the research involves creating a method to assess the market risk associated with biodiversity loss within the equity portfolio. The initial step in this phase involves reviewing potential methods to assess market risk through a literature review.

Subsequently, a specific method is chosen for evaluating market risk in the context of this research. This involves constructing a biodiversity risk factor, which captures the biodiversity risk. After that, we want to estimate the exposure to these risks in the equity portfolio, which is done through estimating the sensitivity through betas. Incorporating both the sensitivity and biodiversity risk factors in the returns, we can simulate the potential losses of the equity portfolio. To measure the biodiversity risks, the possible data on biodiversity indicators is searched and reviewed. This step will consist of a literature review searching for the data. The following step involves selecting the available data to pinpoint indicators capable of indicating physical and transition risks. The biodiversity data undergoes a review to understand its nature and methodology, with a quantitative analysis to assess the nature of the data.

In the last part of the research, the selected method is used to assess the market risk. This starts with calculating the exposure of an equity portfolio to physical and transition biodiversity risk. The equity portfolio used in this research will be globally diversified. Followed by, calculating the influence of biodiversity risk on the market risk of an equity portfolio, which includes both physical and transition risks. The result is a value that represents the market risk including biodiversity risks. Furthermore, the research discusses the implications of the market risk related to biodiversity loss.

1.4 Scope

The scope of this thesis is the focus of the impact of biodiversity loss on equities. However, an investment portfolio can consist of foreign currency, high-yield bond funds, and investment-grade bond funds. As the impact of biodiversity loss on currencies and bonds are difficult to understand, foreign currency and bonds are excluded from our analysis. It is essential to acknowledge that when evaluating the risks of biodiversity loss on the market, this affects currencies and bonds as well. A market shock triggered by a tipping point could lead to defaults, and the correlation in the market may result in a broader impact beyond just stocks. The unpredictable nature of biodiversity loss events could result in losses, introducing tail risks. Consequently, this could result in tail dependencies in the markets, with unforeseen correlation, therefore there can be an impact on the currency and bond markets after such a rare event. Currencies and bonds can be affected by biodiversity loss, but the impact of biodiversity is too difficult to assess for this research at the moment.

1.5 Thesis outline

The structure of the thesis is illustrated in the thesis outline, which discusses each chapter and provides an illustration of the thesis's composition.

Chapter 1: Introduction
The opening chapter addressed the issue of biodiversity loss and its implications for financial institutions. It identified the central problem: a lack in understanding concerning biodiversity indicators and the associated market risks. This challenge led to the formulation of several research questions, which frame the thesis. Subsequently, the design of the thesis was presented, this is created to address the research questions. Finally, the introduction discussed the scope of the thesis.

Chapter 2: Literature review
Chapter two presents the existing literature on the subjects used in this thesis, starting with the

definitions of biodiversity risk, physical risk, and transition risk. Furthermore, it outlines potential methodologies for evaluating market risk. This chapter establishes the definitions, indicators, and methodologies that are applied throughout the thesis.

Chapter 3: Methodology
The methodology chapter delves into the process of evaluating market risk associated with biodiversity loss. It provides a description of the necessary steps involved in this assessment. Furthermore, it discusses the theories and models that support the methodology to give an understanding of the framework.

Chapter 4: Data
The chapter provides an overview of the data used in the thesis and the data concerning biodiversity risk. Initially, the equity portfolios used in this research are examined, shedding light on the construction. Subsequently, an overview of the available data appropriate for assessing biodiversity risk is presented. This includes a specific focus on data that could potentially indicate physical and transition risks.

Chapter 5: Results
The results of the methodology used in the study are discussed in chapter 5, breaking down each phase. This chapter details the outcomes of analyzing the market risk values, offering a comparative insight into market risk with and without the biodiversity risk factors. It shows how incorporating biodiversity risks can impact the market risk associated with an equity portfolio.

Chapter 6: Conclusion and Discussion
The concluding chapter summarizes the research's findings, addressing the main research question and exploring its implications. It includes a reflection on the methodology and approach, identifying areas for potential improvement. The chapter continues with the policy implications and suggestions for future research in this field.

Chapter 2

Literature review

In the literature review, we aim to explore existing literature to address various research questions. The insights gained from these questions will help in identifying biodiversity risks, particularly focusing on physical and transition risks. Moreover, examining established methodologies will provide an overview of evaluating market risks related to biodiversity. The research questions that will be answered with the literature review:

1. *What are appropriate indicators for physical and transition risks related to biodiversity loss?*
2. *What methods are appropriate to use with regard to the assessment of market risks regarding biodiversity loss?*

2.1 Biodiversity indicators

This section is an overview of the existing literature on biodiversity risks. The focus is on the identification of biodiversity risks, specifically on physical and transition risks. To identify these risks, it is important to understand how other studies have identified and indicated these risks. First, there is a broad overview of the papers assessing and defining biodiversity risk. After that, the focus will be on the papers identifying and indicating physical and transition risks.

2.1.1 Biodiversity risk

This subsection specifies how the literature defines and assesses biodiversity-related risk, focusing on financial risk. This research focuses on the identification and assessment of physical and transition biodiversity risk, but understanding how the overall biodiversity-related risk is defined would provide an broad perspective.

OECD (2023) provides a framework for understanding the translation of biodiversity risks into financial risks. It aims to develop methods to understand how biodiversity loss can impact the financial sector, giving different definitions, measurements, and tools. While the paper does not use one of the given assessment methods to assess biodiversity, it offers insights into the indicators, data, and methodologies that could be used. Biodiversity-related financial risks, as defined in this paper, include potential losses for financial industries resulting from biodiversity degradation, which could disrupt portfolio returns. The paper introduces several datasets, such as Exploring Natural Capital Opportunities, Risks, and Exposure (ENCORE), Global Biodiversity model for policy support (GLOBIO), Biodiversity Impact Analytics (BIA)-Global Biodiversity Score (GBS), and Integrated Biodiversity Assessment Tool (IBAT), without specifying for which of the two risks it could be used. ENCORE functions as a database that shows sector-specific impacts and dependencies on ecosystem services across different sectors of the economy. The GLOBIO model calculates the biodiversity footprint measured in Mean Species Abundance (MSA). This leads to the creation of a map containing MSA values corresponding to each human pressure. The BIA-GBS tool assesses the impacts and dependencies of companies. This is achieved by connecting data on economic activities to pressures on biodiversity and translating them into biodiversity impacts. IBAT facilitates access to three global biodiversity datasets. The tool is employed for assessing both impact and dependencies, offering insights into the global conservation status of species. Proposed indicators like MSA, Potentially Disappeared Fraction (PDF), and Species Threat Abatement and Restoration (STAR) offer different approaches to the assessment of biodiversity, with MSA measuring the local biodiversity intactness, PDF represents the percentage of potential species richness loss due to environmental pressures, and STAR highlighting threatened species decline and restoration of ecosystems potential using data from the International Union for Conservation of Nature's Red List Of Threatened Species.

Berger et al. (2018) contribute to the literature by creating a framework for estimating the biodiversity footprint of financial institutions. The paper uses methodologies using the indicators MSA and PDF to quantify biodiversity impact expressed in the number of species. These metrics are evaluated using the GLOBIO model, which calculates biodiversity impacts across various scenarios. Additionally, Pradere et al. (2022) elaborate on the GBS methodology, measuring a company's impacts on biodiversity across its value chain, building upon Berger et al. (2018) framework, using MSA as their key indicator to measure.

Further insights regarding the use of biodiversity indicators and data, come from the work of Agarwala et al. (2022), which explores how nature loss can influence sovereign debt credit ratings and default probabilities, offering various biodiversity scenarios for assessing the decline of nature and its impact. Schrapffer et al. (2022) present a method for evaluating the two-way relationship of biodiversity risks within asset portfolios, emphasizing the interdependence between economic activities and ecosystems. The paper uses data from the ENCORE to establish connections between production processes and ecosystem services. Finally, the method proposed by Wilting and van Oorschot (2017) measures how the supply chains impact biodiversity. They focus on 47 different sectors, using the indicator MSA to assess the impact on the ecosystems.

These studies provide methods to understand companies' biodiversity exposure or impact, though it does not directly address market risks. Indicators that are often used in the literature to indicate the exposure or impact of companies are the MSA and PDF. These indicators are used to calculate certain impacts in the supply chain or assets in portfolios but are not yet linked to the market risk of portfolios. Table 2.1 provides an overview of these papers' approaches to biodiversity risk assessment, showing the various methods used in understanding biodiversity risk. In the next section, we will delve into an examination of physical and transition risks.

Paper	**Indicator used**	**Data set used**	**For whom is the biodiversity risk determined?**
Pradere et al. (2022)	MSA	Exiobase and GLOBIO	Financial institutions
Agarwala et al. (2022)	Gross domestic product (GDP) losses	Data of the scenario from Johnson et al. (2021)	Sovereigns
Berger et al. (2018)	MSA and PDF	Exiobase and GLOBIO	Financial institutions
Schrapffer et al. (2022)	Impact and dependence	ENCORE	Financial institutions
Wilting and van Oorschot (2017)	MSA	GLOBIO	Dutch financial institutions

Table 2.1: Overview of papers defining biodiversity risk

2.1.2 Physical biodiversity risk

This section shows the available literature on physical biodiversity risks. Starting with papers that provide a definition of the risks stemming from physical biodiversity risks. After that, we present papers that specifically assess the physical risks of biodiversity loss in a financial institution.

Definition of physical risk

The paper by OECD (2023) describes physical risks as the dependence of financial institutions, through their lending and investing, on ecosystem services. The physical risks described could be through reduced availability of these ecosystem services, leading to potential risk in the production processes of companies, resulting in a decline of their financial position. The paper states that physical risk entails potential losses in production, service delivery, and the financial standing of a firm due to direct shocks associated with biodiversity loss.

Dasgupta (2021) describes physical risks as linked to human dependence on nature and applied to the financial consequences of adjustments in natural capital. The loss and deterioration of ecosystems can result in the disturbance and potential collapse of crucial ecosystem services. Declined quantity and quality of these services have the potential to harm fixed assets and disrupt business operations by impacting resource availability. Such disruptions lead to direct economic and financial losses for businesses and financial institutions. Physical risks may manifest as short-term event-based occurrences or long-term shifts due to changes in environmental conditions. Besides stating the definition of physical risks, the paper gives interesting examples of physical risks resulting from biodiversity risk, as stated in Box 1. Moreover, the paper states how market risks can be influenced by physical risks, as downgrades in ratings and declines in share prices result from ecosystem disruptions or tipping points.

Box 1. Examples of physical biodiversity risks

Mangroves play a crucial role in protecting against coastal flooding and storm surges. If all existing mangroves were lost, an estimated 39% increase in flooding-affected people and a 16% rise in property damages, approximately $82 billion could occur. (Herweijer et al., 2020)

Wetlands offer vital ecosystem services, including water filtration and flood control. During Hurricane Sandy in 2012, wetlands reduced flood damage costs by over $625 million. Preserving coastal wetlands could annually save the insurance industry $52 billion by minimizing storm and flood damage losses. Coastal wetlands preservation could have significantly reduced the economic impact of Hurricane Katrina in 2005, approximately $150 billion. This underscores the potential for preserving these ecosystems to save the insurance industry billions annually. (Narayan et al., 2017) (Barbier et al., 2018) (Dasgupta, 2021)

NGFS and INSPIRE (2022) follow the same definition and state: *'Physical sources of risk include the degradation of ecosystem services on which economic actors depend'*. Furthermore, it explains that the decline in biodiversity can cause physical risks for financial institutions. Physical risks, such as changes in land use, can adversely affect business operations, impacting profitability and the ability to meet loan obligations. Consequently, financial institutions face market and credit risks as a consequence.

Assessment of physical risk

The study by van Toor et al. (2020) presents one of the earliest studies that assesses biodiversity loss risks in Dutch financial institutions. The paper defines physical risk as diminished access to ecosystem services that pose a threat to financial institutions. The ENCORE database is used to determine a dependence score for each ecosystem, indicating the percentage of the portfolio that is highly or very highly dependent on ecosystems. The assessment involves measuring the exposure of Dutch financial institutions to the sectors that are highly or very highly dependent, considering the shares, corporate bonds, and loans of the financial institutions. This analysis provides insight into the indirect dependence of the Dutch financial sector on ecosystem services. Additionally, the research examines the exposure of Dutch financial institutions to pollination-dependent products, representing a specific physical risk.

Svartzman et al. (2021) conducted a study on the French financial system, quantifying and estimating dependencies and impacts on biodiversity. The physical risks defined in this paper are related to biodiversity and are connected to the direct drivers of biodiversity loss. This research builds upon the methodology of van Toor et al. (2020), using the same approach for assessing the physical biodiversity loss with the ENCORE database.

Building on this, Calice et al. (2021) assess the Brazilian banks for their exposure to biodiversity loss through their lending. The study finds that a collapse of ecosystems can be associated with losses in nonperforming loans relating to physical risks. The physical risks are assessed based on the exposure within their allocation to ecosystem services, using the ENCORE dependence assessment to create a rating on the exposure. The research used the scenario created by the World Bank in Johnson et al. (2021), to estimate the financial risks of bank loans related to biodiversity loss in this scenario.

Building on the research conducted by other central banks, Bank Negara Malaysia et al. (2022) explored the exposure of banks to nature-related financial risks. The analysis assesses the dependence of lending in the financial sector, using the ENCORE database, following the approach used by van Toor et al. (2020).

The research by Kedward et al. (2021) defines physical risks as risks that arise from disruptions to business inputs, operating environments, or consumer demand. The paper by Kedward et al. (2021) uses the ENCORE framework, with its emphasis on dependencies, to explore potential channels through which these physical risks may be transmitted. By identifying dependencies on ecosystem services, the framework offers an indication of which physical risks may be relevant within a portfolio of the ECB.

The paper by Calice et al. (2023) conducts an assessment of banking systems' dependency on ecosystem services across 20 emerging market economies. The analysis in the paper serves as an indicator of the banking sector's vulnerability to biodiversity loss, specifically focusing on biodiversity-related physical risks. The method used for evaluating banks' biodiversity-related physical risk involves examining the loan portfolio allocation to various economic sectors. Drawing from the approaches of van Toor et al. (2020) and Calice et al. (2021) the analysis utilizes the ENCORE database.

Table 2.2 gives a summary of the papers regarding the assessment of physical risks, which shows a clear overview of the definition given and which data sets are used. Moreover, it is indicated for whom the assessment of physical risks is done. The physical indicator is stated in almost every paper as the **'dependence on ecosystem services'**. It states that when a physical collapse due to biodiversity loss occurs, companies dependent on ecosystems become vulnerable to such risks.

The literature does not explicitly state the components of dependence on ecosystems. To address this, we examined the ENCORE database, a resource commonly used in various papers. ENCORE incorporates ecosystem services like genetic materials, flood protection, and disease control in its dependence score. Notably, certain ecosystem services are location-dependent, such as groundwater, which may serve purposes like cooling and chemical processes or washing. The level of exposure to negative consequences associated with this ecosystem service may vary based on geographical sensitivity. Consequently, companies located in more sensitive areas could face greater exposure to physical risks associated with the ecosystems they rely on. On the other hand, in a more stable area, the exposure to the physical risks of this ecosystem service could be less. This means that the location also plays a part in the level of exposure to physical risk.

Paper	Indicator used	Data set used	For whom is the biodiversity risk determined?
van Toor et al. (2020)	Dependence on ecosystem services and dependence on animal pollination	ENCORE	Dutch financial institutions
Svartzman et al. (2021)	Dependence on ecosystem services	ENCORE and Exiobase	French financial institutions
Calice et al. (2021)	Dependence on ecosystem services	ENCORE	Brazilian banks
Bank Negara Malaysia et al. (2022)	Dependence on ecosystem services	ENCORE	Malaysian banks
Kedward et al. (2021)	Dependence on ecosystem services	ENCORE	European Central Bank
Calice et al. (2023)	Dependence on ecosystem services	ENCORE	Central banks

Table 2.2: Overview of papers defining physical biodiversity risk.

2.1.3 Transition biodiversity risk

In this section, the focus is on the transition risks coming from biodiversity loss. The current literature on biodiversity transition risk will be displayed, stating the indicators and datasets. Here, the structure mirrors that of the physical risks, starting with papers that define transition risk and then moving on to papers that assess this risk.

Definition transition risk

OECD (2023) describes transition risks as financial activities that indirectly influence biodiversity, and impact ecosystem services. Emerging government policies relevant to biodiversity or shifts in consumer preferences may influence companies with an impact on ecosystem services to adopt more sustainable business practices. This transformation could also affect financial institutions that invest in these companies, exposing them to transition risk. The companies that are at risk of needing to adapt, thereby are exposed to transition risk, due to government measures and technological advancements aiming to mitigate damage to biodiversity and ecosystem services.

Dasgupta (2021) defines transition risks as risks that emerge as a consequence of a shift toward a more sustainable economy. Transition risks can be triggered by events like the rapid adoption of regulatory policies, technological advancements, or shifts in market preferences, and can lead to losses. Sectors or businesses that fail to adopt technologies or adjust their processes may face the transition risk of financial consequences arising from regulatory changes. Box 2 shows some examples of transition risk caused by biodiversity loss. The paper states that market risks can be influenced by transition risks in two ways: first, long-term profitability undergoes alterations caused by shifts in the market resulting from measures taken to tackle biodiversity loss. Second, regulatory policies connected to mitigating biodiversity loss could lead to the re-pricing of assets.

The paper by NGFS and INSPIRE (2022) states that transition risks arise when there is a misalignment between the impact on biodiversity and efforts aimed at mitigating or reversing biodiversity loss. These efforts incorporate governmental actions, technological advancements, legal proceedings, and shifts in consumer preferences. Likewise, transition risks, such as alterations in policies or consumer preferences, can influence business operations and profitability, especially for companies with processes that negatively impact biodiversity. These risks have the potential to pose threats to individual financial institutions and may combine into systemic financial exposures.

Box 2. Examples of transition biodiversity risks

In 2010, Greenpeace initiated a campaign against Nestle's KitKat brand to highlight its use of palm oil from Indonesian rain forests. This campaign led to a 4% decrease in Nestle's stock value. (McCraine et al., 2019)

In 2008, the Norwegian Pension Fund divested its £500 million stake in the mining business and excluded the company from its funds due to concerns about "severe environmental damage". (Stewart, 2008) (Dasgupta, 2021)

Assessment of transition risk

Following van Toor et al. (2020), companies that have a negative impact on biodiversity and ecosystem services can be exposed to transition risks. The paper argues that the biodiversity footprint of a company offers a perspective on the impact that economic activities have on biodiversity. The analysis used in the paper follows the methodology of Wilting and van Oorschot (2017), the biodiversity footprint is quantified as the reduction in species and population levels within ecosystems. A large biodiversity footprint for financial institutions can act as an indicator of transition risks. The exposure to transition risks is specifically estimated through two approaches: evaluating the possible extension of the protected areas worldwide and assessing the Dutch nitrogen crisis and the associated measures. The first method investigates whether financial institutions lend to or invest in companies in protected areas. Financial institutions face transition risk when providing financing to companies that face risk because they are operating in protected or valuable areas. Transition risk arises when governments appoint new areas as protected, necessitating adjustments or even relocation of business activities, incurring additional costs for the companies involved. To evaluate the vulnerability of Dutch financial institutions, they examine the operations of companies financed by these institutions in protected or valuable areas.

Transition risks are defined as the impact companies have on the ecosystems by Svartzman et al. (2021), using the biodiversity footprint of companies as defined by van Toor et al. (2020). The biodiversity footprint is measured with the indicator MSA, building on the methodology of Wilting and van Oorschot (2017).

Transition risks are identified by Calice et al. (2021) as the risks associated with the exposure to businesses in priority areas in Brazil that are currently unprotected. Hence, this analysis is based on identifying soon-protected areas. They pinpoint valuable areas that may potentially be designated as protected in the near future, taking into account factors such as biodiversity richness. Secondly, they calculate the banks' loan allocation for all firms and pinpoint the establishments of the firms in Brazil, considering geographical information.

Bank Negara Malaysia et al. (2022) describe that Malaysian banks face potential financial transition risks, stemming from their support to companies that adversely affect biodiversity and ecosystem services. The assessment of the impact on ecosystem services follows a methodology similar to that used for evaluating the physical risks on ecosystem services, using the ENCORE database. Transition risks are also defined with the use of protected areas within Malaysia and the exposure to companies operating within these areas. Malaysian banks may face biodiversity transition risk if they finance companies operating in areas of significance to biodiversity.

Transition risk is caused by changes in policy, regulation, technology, or consumer preferences as the paper by Kedward et al. (2021) defines. The ENCORE framework, with its emphasis on impacts, is used as a method for exploring potential channels through which transition risks may be transmitted. Identifying how a financial portfolio contributes to negative biodiversity impacts serves as an estimation for potential sources of transition risk.

Table 2.3 gives an overview of the papers defining and assessing transition risks related to biodiversity loss. In contrast to the physical risk indicator, there are differences in the indicators and assessments used for transition risk. The transition risks may be assessed as the impact it has on the ecosystem services through the ENCORE database, but also as the exposure of companies in protected areas, or as the exposure to certain regulations set by the government.

Paper	**Indicator**	**Data set**	**For whom is the biodiversity risk determined?**
van Toor et al. (2020)	Negative impact on biodiversity and ecosystem services measured by biodiversity footprint, companies in protected areas, and sectors with nitrogen-emitting activities	GLOBIO and FourTwenty-Seven	Dutch financial institutions
Svartzman et al. (2021)	Impact of companies on ecosystems measured by biodiversity footprint	Exiobase, BIA-GBS, and GLOBIO	French financial institutions
Calice et al. (2021)	Exposure to businesses in priority areas	IBAT	Brazilian banks
Bank Negara Malaysia et al. (2022)	Impact on ecosystem services and exposure of companies operating within protected areas	ENCORE and IBAT	Malaysian banks
Kedward et al. (2021)	Impact on ecosystems	ENCORE	European Central Bank

Table 2.3: Overview of papers defining transition biodiversity risk

2.2 A model to estimate market risk

This research aims to estimate the market risk associated with biodiversity loss. To quantify this market risk, it is essential to develop a model. The selection of an appropriate method will be done by a review of existing literature. Through this literature review, we search for various existing methods to develop a model that estimates the market risk.

Market risk refers to the risk associated with fluctuations in financial market prices, indicating the unpredictability of an asset's selling price. This market risk varies based on the asset type in question. The method for evaluating market risk is determined by the data characteristics and how a portfolio's value changes in response to market price fluctuations. (Corelli, 2019)

The research on the market risk associated with biodiversity loss is new. Given the uncertain nature of climate change, insights from this area may offer valuable methodologies for assessing market risk due to biodiversity loss. Scenario analysis is a potential approach for evaluating biodiversity risk, illustrating the economic implications of biodiversity loss through various scenarios. However, as the analysis in Appendix A shows, there currently are no specific scenarios addressing biodiversity's impact on the equity market, and as a result, scenario analysis will not be utilized in this research.

Another way to assess the market risk is through calculating the Value at Risk (VaR) or Expected Shortfall (ES). VaR and ES are metrics designed to estimate the overall risk of a portfolio in a single figure. Essentially, VaR indicates the maximum loss expected over time T that a confidence level (X%) will not be surpassed. The calculation of VaR can be based on the probability distribution of either gains or losses within a time frame (T). Hull (2018) discusses a simplistic assumption, that the change in the value of the portfolio over a certain time horizon follows a normal distribution. This assumption is typically inadequate, as practice often shows distributions with fatter tails. Nonetheless, it is useful to explore the implications of this assumption. The VaR is then calculated with the following equation, as discussed by Hull (2018):

$$VaR = \mu + \sigma N^{-1}(X) \tag{2.1}$$

Where the mean is denoted by μ, the standard deviation is represented by σ, X denotes the confidence level, and N^{-1} represents the inverse cumulative normal distribution. While VaR examines the extent of potential losses, ES estimates how much might be lost when things get worse than expected. To determine ES, one must first calculate VaR. ES represents the average expected loss over time, given that losses surpass the VaR threshold. Hull (2018) also discusses the implications of the assumption of normality for the calculation of ES. The ES can be expressed as:

$$ES = \mu + \sigma \frac{e^{-Y^2/2}}{\sqrt{2\pi}(1-X)} \tag{2.2}$$

where Y represents the Xth percentile point of the standard normal distribution.

Dowd (2003) and Corelli (2019) describe how to calculate the market risk with the use of VaR for a single stock i. The return, R_i, of the stock i, is linked to the overall stock market return R_m using the equation:

$$R_i = \alpha + \beta_i R_m + \varepsilon \tag{2.3}$$

Here, α is a constant unique to the firm, β_i is a coefficient linking R_i to R_m, and ε is a random element specific to the firm. This is possible because the return on the stock i is connected to the market return R_m via a relationship defined by the Capital Asset Pricing Model (CAPM). While the direct volatility is not known, the variance of the stock i can be estimated based on the variance of the market:

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma_\varepsilon^2 \tag{2.4}$$

The equation splits the variance into a market-related component $\beta_i^2 \sigma_m^2$ and a firm-specific component σ_ε^2. Assuming a normal distribution with zero mean and an investment of amount y in the stock, the VaR for the stock i is calculated as:

$$VaR_i \approx -\alpha_{cl} y \sigma_i = -\alpha_{cl} y \sqrt{\beta_i^2 \sigma_m^2 + \sigma_\varepsilon^2} \tag{2.5}$$

where the cl is defined as the confidence level of the VaR. The a_{cl} represents the z-score corresponding to the selected confidence level. Both the market variance σ_m^2 and the β_i of the stock are usually publicly available, allowing for the estimation of $\beta_i^2 \sigma_m^2$. If we also have data on the firm-specific variance σ_ε^2, we can directly estimate the VaR as shown above. For well-diversified portfolios, the idiosyncratic risks are largely neutralized, and we could approximate the VaR for stock i by treating σ_ε^2 as zero:

$$VaR_i \approx -\alpha_{cl} y \beta_i \sigma_m \tag{2.6}$$

This method, known as 'market beta' mapping, simplifies the estimation of the VaR for a stock by relying on market volatility and the firm's market beta only. The CAPM model is known as a 1-factor model because it represents just one risk factor that explains the returns, namely the market factor.

The model created by Fama and French (1993) expands the CAPM by incorporating factors accounting for a size and a value effect. They named their size factor Small Minus Big (SMB) and their value factor High Minus Low (HML). The value factor makes a distinction between book-to-market, where high book-to-market is represented as value companies, and low book-to-market as growth companies. SMB and HML are both long-short factors, representing portfolios that hold simultaneous \$1 long positions and \$1 short positions in equities. Specifically, HML = \$1 in value equities (long) - \$1 in growth equities (short), focusing on the better performance of value equities over growth equities.

The Fama-French model maintains positions in both SMB and HML factor portfolios, alongside a position in the market portfolio, as the original CAPM. The model expanded the CAPM equation to include both a size and a value factor. The Fama-French model can be assessed by running the following time series regression:

$$R_t - R_{f,t} = \alpha + \beta_1 (R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \tag{2.7}$$

which integrates the SMB and HML factors into the traditional market factor model. (Ang, 2014)

The HML portfolio is designed to copy the risk factor in returns associated with book-to-market equity. The median size of NYSE equities is utilized to divide equities into two categories: small and large (S and B) equities. HML is computed each month by subtracting the average returns of the two low book-to-market equity portfolios (S/G and B/G) from the average returns of the two high book-to-market equity portfolios (S/V and B/V). Resulting in the formula given in French (2023a):

$$HML_t = \frac{S/V_t + B/V_t}{2} - \frac{S/G_t + B/G_t}{2} \tag{2.8}$$

The components of HML consist of returns from portfolios with high and low book-to-market ratios, both balanced to have approximately the same average size. This ensures that the resulting difference in returns is predominantly independent of the size factor and instead highlights the distinct return patterns of firms with high and low book-to-market ratios (Fama & French, 1993). The average return of these factors shows the average extra return investors receive, known as the risk premium. This is what investors demand for taking on extra risk. So, if the average return of HML is positive, it means there is a positive risk premium. This indicates that investors are getting extra returns for investing in high book-to-market companies. On the other hand, if the average return is negative, it means there is a negative risk premium, suggesting investors might not need extra returns for their risky investments.

Having explored different methods for estimating market risk, we now turn to the literature to find ways to integrate biodiversity risk into one of these approaches. A couple of papers extend the CAPM formula with a climate risk factor. These papers include a carbon or climate risk factor, in this same way we could include a biodiversity risk factor. Roncalli et al. (2021), Görgen et al. (2020), and Huij et al. (2023) use the Fama-French model to incorporate the carbon risk factor into the CAPM model. These methods could also be used to incorporate a biodiversity risk factor into the CAPM model, and with the adjusted CAPM model we could calculate the market risk regarding biodiversity risk.

Roncalli et al. (2021), Görgen et al. (2020), and Huij et al. (2023) construct a carbon risk factor the same way the Fama-French model constructs its HML risk factor. Due to this, the papers construct different portfolios which are separated by their carbon emissions. Resulting in long portfolios including companies with relatively high emissions and short portfolios comprising companies with relatively low emissions. This results in the transformation of the CAPM formula into a multi-factor model that assesses not only size and value but also carbon risk. They introduce a method to capture the market risk, as the multi-factor model provides a framework to assess the market movements coming from changes in the factor. Similarly, this approach could be used to include a biodiversity risk factor.

The addition of the carbon risk factor results in a return that is influenced by the market, size, value (book-to-market), and carbon. Huij et al. (2023) add besides these Fama-French risk factors also the momentum factor from Carhart (1997). The momentum effect, suggests that equities with high historical returns continue to ascend while those with poor historical returns persist in underperforming, as discussed by Ang (2014).

By incorporating the carbon risk factor alongside factors from the Fama and French model and the momentum, Huij et al. (2023) analyze the exposure of individual equities to climate transition risks, estimating the carbon beta. This is done by a time regression, resulting in the carbon beta that represents the sensitivity of the equity to the carbon risk factor. The findings suggest that companies larger in size, more innovative, and more profitable tend to have lower climate risk exposure, while those that are capital and carbon-intensive exhibit higher exposure. The climate risk is priced in equity returns, meaning that there is a carbon risk premium. This research estimates an additional annual return of 1.15% when there is an increase in the carbon beta.

Following this methodology, there are some different ways to estimate the carbon risk factor. Yang et al. (2023) changed the CAPM formula by incorporating a news-based climate risk factor. This research explores the importance of climate-related news for investors to construct the Fama-French long-short portfolios. This involves categorizing equities according to how their returns respond to the climate news factor, followed by forming a portfolio that takes advantage of these insights by going long on equities highly sensitive to climate news and short on those with minimal sensitivity. This method shows a different methodology to construct the carbon risk factor than using the carbon emissions. This could also be used to create the biodiversity risk factor, incorporating biodiversity news to make the portfolios.

Giglio et al. (2023) incorporate the biodiversity news to create such a biodiversity risk factor. They create a new index based on news that shows how overall biodiversity risk changes over time. The findings reveal that exposure to negative biodiversity news and these biodiversity risks differs significantly across industries. Moreover, they discover that biodiversity risks are already affecting stock prices: the returns of investment portfolios sorted based on their biodiversity risk exposure, give a positive risk premium. However, their survey shows that investors do not believe current stock prices accurately reflect the risks associated with biodiversity loss. Giglio et al. (2023) show that there is a risk premium resulting from biodiversity risk based on their biodiversity risk exposure, they also use the Fama-French factors in their methodology. The news-based assessments lead to a biodiversity risk factor. However, in this research we want to examine the company-specific physical and transition biodiversity data. This assessment by Giglio et al. (2023) does not incorporate the biodiversity risk factor into calculating market risk. In contrast, our research aims to quantify market risk stemming from these biodiversity risk factors.

These methodologies to incorporate the carbon risk factor and the carbon beta into the Fama-French model to estimate the return on equity could help us estimate the market risk of biodiversity loss. In the same way, we could incorporate a biodiversity risk factor and biodiversity beta into the Fama-French model. Following the method, we could create a return formula for a stock that incorporates the biodiversity risk. These returns can be simulated, giving us different returns under different values of the biodiversity risk factors and the other risk factors.

Modifying the CAPM formula to include an extra Fama-French-inspired factor is a common approach in research for assessing carbon risk. Alternatively, market risk assessment could involve changing the VaR method. Capelli et al. (2023) integrate Environmental, Social, and Governance (ESG) risk into the VaR framework, suggesting that incorporating biodiversity risk into the VaR could also be possible. Capelli et al. (2023) introduce a new risk metric, VaR_{ESG}, that combines the market risk metric, VaR, with ESG considerations. This method could be attractive to incorporate a biodiversity risk into the VaR, however the paper is quite vague on the precise methodology it follows. Therefore, it is difficult to follow the method and due to this, we are not going to use it in this research to incorporate biodiversity risk in the VaR.

2.3 Conclusion

In the literature review, we searched for the answer to two research questions. Resulting in different definitions and methods that can be used in this research.

1. *What are appropriate indicators for physical and transition risks related to biodiversity loss?*

   As noticed in the literature, physical risk can be interpreted as a measure of a company's dependency on ecosystem services. Additionally, the geographical location of companies can influence the severity of a physical collapse. In contrast to the physical risk indicator, there are differences in the indicators and assessments used for transition risk. The transition risks may be assessed as the impact it has on the ecosystem services through the ENCORE database, but also as the exposure of companies in protected areas, or as the exposure to certain regulations set by the government. Transition risk can be evaluated in three different ways, as shown by the literature: impact on ecosystem services, exposure to sensitive areas, and exposure to specific biodiversity-related regulations.

2. *What methods are appropriate to use with regard to the assessment of market risks regarding biodiversity loss?*

   The main approach found in the literature for evaluating carbon risk involves incorporating a carbon risk factor into the Fama-French model. This allows for the estimation of a carbon beta through techniques such as time regression. Similarly, when assessing biodiversity risk, this methodology can be applied. By integrating a biodiversity risk factor into the Fama-French model, it becomes also possible to establish a biodiversity beta. Given the objective of assessing market risk associated with biodiversity risk, both betas and risk factors are important in this calculation. These metrics allow for the computation of portfolio returns, which, when considering the worst percentile, provides us with both VaR and ES. Therefore, by constructing betas and biodiversity risk factors, we can derive the VaR and ES for an equity portfolio regarding biodiversity risk.

Chapter 3

Methodology

This chapter will outline the methodology that will be used in this study. The method consists of three key phases: estimating the biodiversity risk factors from the equity returns and their biodiversity scores, calculating the biodiversity beta values for individual equities and the equity portfolio as a whole, and determining the corresponding portfolio market risk which incorporates the biodiversity risk factors and exposures. Each of these steps will be detailed in this chapter, we will be able to address the research question:

How can market risk be analyzed concerning physical and transition biodiversity risks?

Figure 3.1 illustrates in a flowchart the main steps in the methodology used to calculate the VaR and ES. The first step involves estimating the biodiversity risk factors, shown in yellow. This includes creating separate risk factors for both physical and transition risks. These risk factors are then used to calculate betas for each risk factor using an Ordinary Least Squares (OLS) regression, depicted in orange. This estimates the sensitivity of the equity portfolio to each risk factor. The final step involves the simulation of potential losses of the equity portfolio and the estimation of the VaR and ES metrics, shown in red. This simulation is achieved by simulating each risk factor based on their distribution. From these simulated portfolio returns, we can calculate the VaR and ES of the equity portfolio. This provides insight into the market risk of the risk factors, incorporating biodiversity risk, on the equity portfolio.

The data required for the methodology is highlighted in blue. This includes the composition of specific portfolios. Stock prices within these portfolios are utilized to compute stock returns. Furthermore, exposure to physical and transition risks is necessary for constructing the risk factors, which depend on the level of risk exposure to each of them. These datasets will be described in the following data chapter.

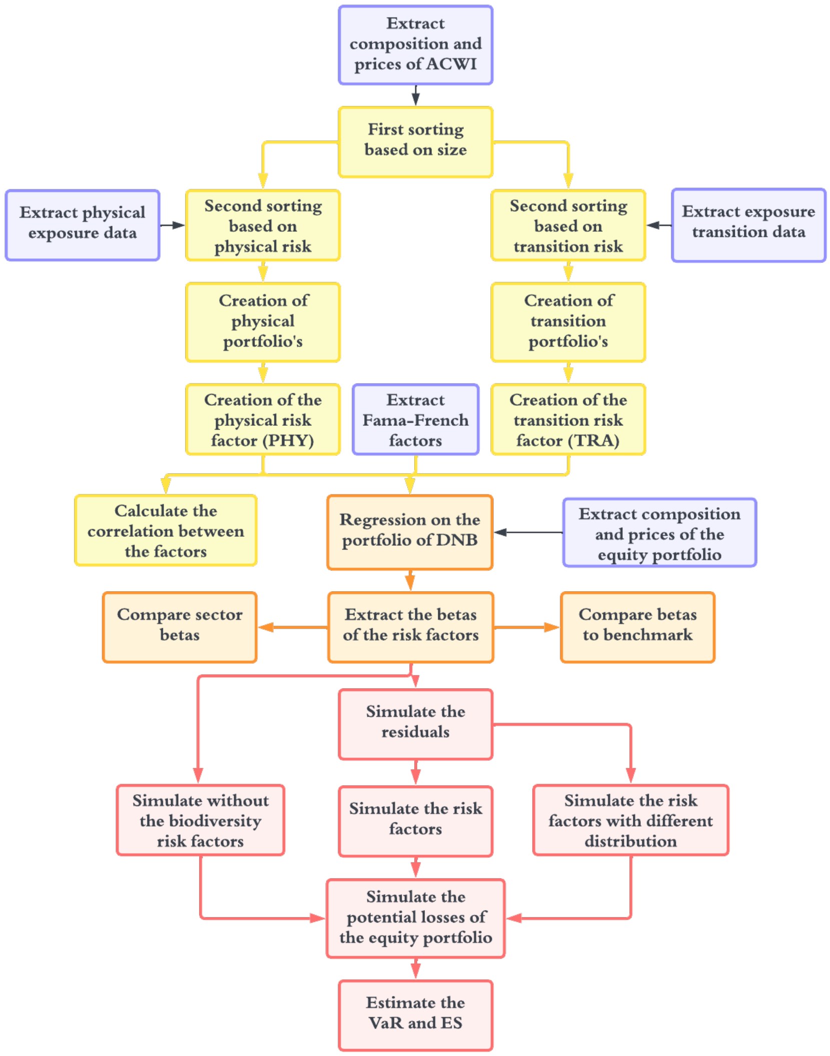


Figure 3.1: Method

3.1 Biodiversity risk factor

In this section, we discuss how to capture both physical and transition risk factors. Here, we follow the HML portfolio methodology of Fama and French (1993) to establish a biodiversity risk factor. This methodology is also used by Huij et al. (2023) to capture a carbon risk factor. To capture the physical and transition risk factors, we construct two HML portfolios, a High Physical - Minus - Low Physical (PHY) and a High Transition - Minus - Low Transition (TRA) portfolio. Where the high-risk portfolios tell us that the equities have negative exposure to biodiversity loss. On the other hand, low-risk portfolios mean less exposure to biodiversity loss. The high and low-risk portfolios will be self-financing portfolios that take a long position in the equities with the highest scores and a short position in the equities with the lowest scores, following the methodology of the HML portfolio of Fama and French (1993). Where the research of Giglio et al. (2023) focuses on the biodiversity news to create high and low-risk portfolios, this research focuses on company-specific physical and transition risks to create high and low-risk portfolios.

To create biodiversity high and low-risk portfolios, the All Country World Index (ACWI) is chosen, as this represents a wide range of stocks, more than 2,800 stocks, in 23 developed markets and 24 emerging markets. This index gives a representation of how the worldwide stock market reacts and shows the physical and transition biodiversity factors worldwide. (MSCI, 2024)

Following Huij et al. (2023), we first sort on the size of companies, then on the biodiversity physical and transition risk. To ensure that the difference in returns mostly is not influenced by company size but rather shows how companies with high and low biodiversity risk differ in returns, we should sort the companies by size. It is possible to do the first sorting based on the other factors, such as the market or the value of the company. This would neutralize those factors out of the biodiversity risk factors. In this research, we follow the methodology of Huij et al. (2023), therefore the portfolios are sorted based on size. It would be interesting to see how the biodiversity risk factors perform when the first sorting is based on different factors. However, this lies outside the scope of this research.

Sorting the stocks by size, which is represented as the market value, can be executed in various ways, one approach being sorting by the median, as followed by Huij et al. (2023). An alternative method for sorting stocks by size involves selecting a percentile of both the largest and smallest companies. Currently, there is no established literature defining a specific percentile for creating such portfolios. Fama-French constructs its HML factor in French (2023a) with the 10th percentile, large companies are in the top 90%, and small companies are in the bottom 10%. The second sorting results from the physical and transition data, which represents the exposure to both risks. This sorting of the high and low-risk equities depends on the nature of the data of both risks.

The double sorting results in four portfolios for both physical risk factor (PHY) and transition risk factor (TRA), namely big/high biodiversity score (B/HP, B/HT), small/high biodiversity score (S/HP, S/HT), big/low biodiversity score (B/LP, B/LT), and small/low biodiversity score (S/LP, S/LT). The return of the portfolios on day t can then be described as:

$$PHY_t = \frac{R_{B/HP,t} + R_{S/HP,t}}{2} - \frac{R_{B/LP,t} + R_{S/LP,t}}{2} \tag{3.1}$$

$$TRA_t = \frac{R_{B/HT,t} + R_{S/HT,t}}{2} - \frac{R_{B/LT,t} + R_{S/LT,t}}{2} \tag{3.2}$$

In this research, we decided to use weekly equal-weighted[1] return data over a period of three years. This results in weekly prices for the years 2021, 2022, and 2023, totaling 156 weeks. The average return on the biodiversity risk factors show the average risk premium investors receive due to the risk they take when investing in high biodiversity risk equities. When the risk premium is positive, the investors receive a risk premium for the biodiversity risk. A negative risk premium means that investors do not receive extra returns for their risky biodiversity equities.

As we estimate the biodiversity risk factors, we can estimate the excess return on stock i in the equity portfolio with the Fama-French factors and both biodiversity risk factors, which is also done by Huij et al. (2023) and Görgen et al. (2020) which incorporate a carbon risk factor in the Fama-French equation. This entails the Excess return on the market portfolio (RMRF). size (SMB), value (HML), and Momentum (UMD). The momentum was added to the Fama-French by Carhart (1997). The momentum effect, which suggests that stocks with high historical returns continue to ascend while those with poor historical returns persist in underperforming, is incorporated into the factor model, as discussed by Ang (2014). The method of Huij et al. (2023) incorporates the momentum factor, which is also incorporated in this research. The formula that calculates the excess return on stock i is:

$$R_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} UMD_t + \beta_{5,i} PHY_t + \beta_{6,i} TRA_t + \varepsilon_{i,t} \tag{3.3}$$

where $R_{i,t}$ is the excess return on week t on stock i. The stock's adjusted outperformance is denoted as a_i, and the $\beta' s$ represent the sensitivity to their risk factor. Moreover, $RMRF_t$, SMB_t, HML_t, UMD_t, PHY_t, and TRA_t indicate the weekly returns on the market, size, value, momentum, physical risk factor, and transition risk factor. Lastly, the $\varepsilon_{i,t}$ refers to the residual term.

Having computed both PHY and TRA, it's insightful to examine their correlations with the Fama-French factors, which is also done by Huij et al. (2023). Correlation explains how the factors move relative to each other, providing insights into their independence. Correlations with positive values indicate consistency in movement and negative values mean opposing movements. A correlation close to 1 indicates a strong relationship, while closeness to zero suggests minimal correlation.

[1] Fama and French (1993) and Huij et al. (2023) use value-weighted returns, this change in weighting could influence the results of the biodiversity risk factors in this research. It would be interesting for future research to see how the biodiversity factors perform with this value weighting.

3.2 Biodiversity betas

The next step is to estimate the physical and transition biodiversity beta based on Equation 3.3. The method of Huij et al. (2023) runs a time series regression of the returns of stock i while controlling RMRF, SMB, HML, and UMD to estimate the carbon beta. We follow the methodology of Huij et al. (2023) to estimate the physical and transition beta with a time series regression, with the RMRF, SMB, HML, and UMD the Fama-French returns on the same 156 weeks. As there is more than one factor that influences the return of stock i, we conduct a multiple linear regression. In this situation, we use one of the standard regression models, namely OLS to conduct the multiple linear time regression. OLS is a widely used method for calculating the coefficients in linear regression models that illustrate the connection between one or several independent numerical variables (RMRF, SMB, HML, UMD, PHY, and TRA) and a dependent variable (return of stock i).

In this time series regression, we use the 3-years with weekly data. Giving us 156 weekly return observations for each of the stocks i in the equity portfolio. This regression will return the betas for each of the equities on the different risk factors. An analysis will be done if the physical and transition betas are indeed significant, so if the stocks are really sensitive to physical and transition risk.

The betas of each stock can be combined to determine the betas of the portfolio. The portfolio betas are determined by multiplying the beta of each stock with the weight of the stock in the portfolio. The aggregation of all these weighted betas results in the beta of the portfolio. As the portfolio changes in composition from time to time, the weights of the stocks in the portfolio also change. The estimation of the portfolio beta is done with the weights at the end of 2023, from the 29th of December. However, if we exclude some stocks from the regression, the weights do not add up to 100%. Therefore, we need to scale the weights back to 100%, by dividing the weights through the aggregated weight of the included stocks.

The time series regression results in a beta for the equity portfolio and sector-weighted betas, however, these are standing-alone values. The beta represents the movement with the risk factors and could also represent some exposure to the physical and transition factors. On the other hand, we have nothing to compare it to, so we do not know if the beta of the portfolio is high or low relative to other indexes. Therefore, we want to compare the biodiversity betas of the equity portfolio to the betas of the ACWI index. The previous steps will also be conducted for the ACWI, but instead, the returns and weights of the ACWI are used. The ACWI returns are excess returns based on local prices, to calculate the excess returns we subtract the risk-free rate from the returns.

3.3 Estimating market risk

The final step is to simulate the potential losses of the equity portfolio and to estimate the VaR and ES. The estimation of the VaR and ES is done by incorporating both biodiversity risk factors. The outcome will give an estimation of the market risk in the equity portfolio regarding biodiversity loss. Equation 3.3 is used to simulate the potential losses of the equity portfolio.

As explained in the previous chapters, the risk factors are estimated with a long-short portfolio or extracted from the Fama-French factors. The betas are calculated with the help of the OLS time series regression, resulting in all the betas for each stock in the portfolio. After doing all these steps, we will combine all the information to simulate the returns for each stock. The simulation is done in three steps, first, we start with the simulation of the residuals. In the second step, we simulate the risk factors. After which we combine both simulations and create the returns on the equity portfolio, The last step is then to calculate from the returns of the portfolio the VaR and ES.

In this simulation, we make the assumption that both risk factors and residuals follow a normal distribution, denoted as $\mathcal{N}(\mu,\sigma)$. However, in practical scenarios, this assumption often proves inaccurate, with factors and residuals displaying thicker tails or skewness. When using the assumption of a normal distribution, we could compute the VaR using the formulas outlined in Chapter 2.2, as expressed in Equation 2.5. In this case, there would be no need to simulate risk factors and residuals. Nonetheless, given the frequent deviation from normality in risk factors and residuals, sensitivity tests to evaluate how alternative distributions impact VaR is necessary. Consequently, we simulate the risk factors and residuals to enable distribution transformation, which is difficult to achieve with Equation 2.5.

Simulation of the residuals

The first step is to simulate the residuals, ε_i. The residuals are extracted from the biodiversity time series regression, which is done in the previous step. This represents the difference between the actual return of the stock and the predicted value of the times series regression. The predicted return is calculated by multiplying the risk factor with the beta of the risk-return.

The risk factors are represented as six risk factors in each week for the 156 weeks, which gives matrix **F**. This matrix represents the returns of each risk factor, which is extracted from the Fama-French database or calculated in 3.1. Where t indicates the week, k the risk factor, and $f_{t,k}$

the return of risk factor k in week t.

$$\mathbf{F} = \begin{bmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,k} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ f_{t,1} & f_{t,2} & \cdots & f_{156,6} \end{bmatrix}$$

The betas are represented for the six risk factors for all the stocks in the equity portfolio. This results in matrix $\mathbf{X}$, where k indicates the risk factor, i is a stock, and $\beta_{i,k}$ indicates the beta value for stock i of risk factor k:

$$\mathbf{X} = \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \cdots & \beta_{1,k} \\ \beta_{2,1} & \beta_{2,2} & \cdots & \beta_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{i,1} & \beta_{i,2} & \cdots & \beta_{i,6} \end{bmatrix}$$

The predicted returns, $\mathbf{M}$, are calculated by multiplying the return of the risk factor by its beta for each week.

$$\mathbf{M} = \mathbf{X} \times \mathbf{F}^T$$

This equation results in the matrix $\mathbf{M}$, where $m_{i,t}$ indicates the predicted return for stock i in the week t.

$$\mathbf{M} = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,t} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,t} \\ \vdots & \vdots & \ddots & \vdots \\ m_{i,1} & m_{i,2} & \cdots & m_{i,156} \end{bmatrix}$$

The residual is calculated by subtracting the actual return from the predicted return for each stock in each week. Where $\mathbf{R}$ is the matrix of each actual returns of the stocks in the equity portfolio in week t:

$$\mathbf{E} = \mathbf{R} - \mathbf{M}$$

This subtraction results in the matrix of $\mathbf{E}$, where $\varepsilon_{i,t}$ indicates the residual for stock i in week t:

$$\mathbf{E} = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \cdots & \varepsilon_{1,t} \\ \varepsilon_{2,1} & \varepsilon_{2,2} & \cdots & \varepsilon_{2,t} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{i,1} & \varepsilon_{i,2} & \cdots & \varepsilon_{i,156} \end{bmatrix}$$

The simulated residuals are assumed to have a normal distribution with a mean of zero. The other assumption is that there is no correlation between the residuals of the stocks, as the assumption is that the residuals are stock-specific. In theory, it can be that there is a correlation between the residuals, however, this correlation lies outside the scope of this thesis. Therefore the residuals are simulated from a normal distribution with $\varepsilon_i \sim \mathcal{N}(0, \sigma^2_{\varepsilon_i})$.

The $\sigma^2_{\varepsilon_i}$ is calculated based on the variance of residuals of each stock. Therefore we take the variance of the residuals of each stock. Leaving us with a matrix of the variances of residuals, namely $\mathbf{V}$.

$$\mathbf{V} = \begin{bmatrix} \sigma^2_{\varepsilon\,1} \\ \sigma^2_{\varepsilon\,2} \\ \vdots \\ \sigma^2_{\varepsilon\,i} \end{bmatrix}$$

The matrix $\mathbf{V}$ gives the input for the simulation of the residuals for each stock. We simulate n random residuals for stock i, based on the assumption of $\varepsilon_i \sim \mathcal{N}(0, \sigma^2_{\varepsilon_i})$. This results in the matrix $\hat{\mathbf{E}}$, which represents the simulated residuals. The simulated residuals are indicated as $\hat{\varepsilon}_{i,n}$, which represents the residual for simulation n for stock i.

$$\hat{\mathbf{E}} = \begin{bmatrix} \hat{\varepsilon}_{1,1} & \hat{\varepsilon}_{1,2} & \dots & \hat{\varepsilon}_{1,n} \\ \hat{\varepsilon}_{2,1} & \hat{\varepsilon}_{2,2} & \dots & \hat{\varepsilon}_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\varepsilon}_{i,1} & \hat{\varepsilon}_{i,2} & \dots & \hat{\varepsilon}_{i,n} \end{bmatrix}$$

Simulate risk factors

The second step is to simulate each risk factor k based on its mean and its covariance matrix. We will simulate each risk factor n times, resulting in n returns for each risk factor. In this simulation, we assume that all the risk factors have a normal distribution. In theory, we know that these distributions often have a fatter tail, showing that a normal distribution often does not fit. However, in this simulation we will assume that the risk factors do have a normal distribution, to give a picture of the market risk under this condition.

Based on the normality assumption we extract n random simulations for each risk factor from the multivariate normal distribution. The simulated values for each risk factor k have a $\mathcal{N}(\mu_k, \Sigma_k)$ distribution, based on their mean and the covariance matrix. Resulting in matrix $\hat{\mathbf{F}}$, which represents the simulated returns from the risk factors. Where we have $\hat{f}_{n,k}$ that indicates the simulated returns for risk factor k for simulation n.

$$\hat{\mathbf{F}} = \begin{bmatrix} \hat{f}_{1,1} & \hat{f}_{1,2} & \cdots & \hat{f}_{1,k} \\ \hat{f}_{2,1} & \hat{f}_{2,2} & \cdots & \hat{f}_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{f}_{n,1} & \hat{f}_{n,2} & \cdots & \hat{f}_{n,6} \end{bmatrix}$$

The part of the returns of the equity portfolio without the residuals needs to be calculated, we have to multiply the simulated risk factors with the betas. The matrix $\mathbf{X}$ represents these betas values for stock i and risk factor k, which is multiplied by $\hat{\mathbf{F}}$.

$$\mathbf{S} = \mathbf{X} \times \hat{\mathbf{F}}^T$$

Resulting in a matrix $\mathbf{S}$ that represents the simulated returns of each stock as $s_{i,n}$ for stock i in the portfolio at simulation n.

$$\mathbf{S} = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,n} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{i,1} & s_{i,2} & \cdots & s_{i,n} \end{bmatrix}$$

The returns of each stock i are then calculated by adding the simulated returns and the simulated residuals for each stock.

$$\hat{\mathbf{R}} = \mathbf{S} + \hat{\mathbf{E}}$$

Resulting in matrix $\hat{\mathbf{R}}$, which represents the simulated return $\hat{r}_{i,n}$ of each stock i at simulation n.

$$\hat{\mathbf{R}} = \begin{bmatrix} \hat{r}_{1,1} & \hat{r}_{1,2} & \cdots & \hat{r}_{1,n} \\ \hat{r}_{2,1} & \hat{r}_{2,2} & \cdots & \hat{r}_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{r}_{i,1} & \hat{r}_{i,2} & \cdots & \hat{r}_{i,n} \end{bmatrix}$$

Calculation of VaR

The estimation of the VaR is done by calculating the potential losses of the equity portfolio. At the moment, we have the return per stock, we want to calculate the return of the portfolio. Therefore we have to multiply the returns with the weight of each stock w_i. In the process, we excluded some stocks that do weight in the portfolio. This would mean that the sum of the weights is not 100%. Due to this, we have scaled the weights, so that the sum of all the weights is 100%. The matrix $\mathbf{W}$

is created with the weight of each stock i.

$$\mathbf{W} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_i \end{bmatrix}$$

The returns of the equity portfolio are calculated by multiplying the weight of each stock w_i by its return $\hat{r}_{i,n}$:

$$\mathbf{P} = \mathbf{W}^T \times \hat{\mathbf{R}}$$

This results in the matrix **P**, where p_n indicates the portfolio return of simulation n.

$$\mathbf{P} = \begin{bmatrix} p_1 & p_2 & \dots & p_n \end{bmatrix}$$

Matrix **P** represents n simulated portfolio weekly returns of the equity portfolio. The weekly VaR is calculated by taking the 99% percentile of the weekly returns. The 99% is used because this is used in DNB's calculations of the market risk. The 99%-VaR is the weekly return that is the worst 1% of the weekly returns. It is assumed that the returns of the equity portfolio on successive days follow independent, identically distributed normal distributions with a mean of zero. Then, following Hull (2018), we can say:

$$\text{Annual VaR} = \text{Weekly VaR} \times \sqrt{52} \tag{3.4}$$

The 99%-ES results from calculating the 99%-VaR when we estimate the value that lies at the worst 1% we can extract the values that lie below this percentile. The 99%-ES is then the average of the values that lie below the 99% percentile. The annual ES is estimated based on the same assumption of independent, identically distributed normal distribution, which results in:

$$\text{Annual ES} = \text{Weekly ES} \times \sqrt{52} \tag{3.5}$$

3.3.1 Sensitivity analysis

The next step is to do a sensitivity analysis. The assumption is that the risk factors have a normal distribution, which is in practice often not true. The focus of the research is on the physical and transition risk factors. In this section, we want to do a sensitivity analysis on both factors with a fatter tail. Both factors will be transformed into a student t-distribution, which has a fatter tail than the normal distribution. The student t-distribution is dependent on the degrees of freedom. The higher the degrees of freedom, the more it will transform into a normal distribution. The lower the degrees of freedom, the fatter the tail.

We follow the same process discussed in the previous chapter, however, we transform the simulations of the physical and transition risk factors. In the normal situation, we have the matrix $\hat{\mathbf{F}}$, with all returns generated from the normal distribution $\mathcal{N}(\mu_k, \Sigma_k)$. In this sensitivity analysis, we transform the returns of the physical and transition factors to a student t-distribution, following the method of Dimitrov and van Wijnbergen (2023). This is done with the formula:

$$\mathbf{St}(\nu) = \mathbf{U} \times \sqrt{\frac{\nu}{\mathbf{H}}} \tag{3.6}$$

Where $\mathbf{H} \sim \chi^2(\nu)$ and ν depicts the degrees of freedom. This formula will be used to transform the normal distribution $\mathbf{U}$ to student t-distribution $\mathbf{St}$.

As discussed the degrees of freedom ν play an important part in the simulation as to how fat-tailed the transformed risk factor will look like. We will simulate the degrees of freedom from 3 to 30. The transformation is done to the matrix $\mathbf{B}$ which only consists of the physical and transition factor. Where $b_{n,2}$ represents the simulated weekly return of biodiversity risk factor 2 in simulation n, under the assumption of normality.

$$\mathbf{B} = \begin{bmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \\ \vdots & \vdots \\ b_{n,1} & b_{n,2} \end{bmatrix}$$

The first step in the transformation is to standardize each column with its mean and standard deviation. The standardization is done to make the factors on the same scale as the chi-square random values. For the first column, we use the following formula, where we first subtract the mean and then divide it by its standard deviation, which results in the matrix $\mathbf{U}_1$ for the first column.

$$\mathbf{U}_1 = \left(\begin{pmatrix} b_{1,1} \\ b_{2,1} \\ \vdots \\ b_{n,1} \end{pmatrix} - \mu_{b_1} \right) \times \frac{1}{\sigma_{b_1}}$$

We do the same for the second column but with its own mean and standard deviation. This results in matrix $\mathbf{U}$ with two columns with standardized values, u, which we can transform into a student t-distribution with Equation 3.6.

$$\mathbf{U} = \begin{bmatrix} u_{1,1} & u_{1,2} \\ u_{2,1} & u_{2,2} \\ \vdots & \vdots \\ u_{n,1} & u_{n,2} \end{bmatrix}$$

Transforming the matrix **U** means that we have to multiply it with $\sqrt{\frac{\nu}{\mathbf{H}}}$, where we have to extract random values from the distribution of $\mathbf{H} \sim \chi^2(\nu)$. This results in the matrix **H**, with values, h, from the chi-square distribution.

$$\mathbf{H} = \begin{bmatrix} h_{1,1} & h_{1,2} \\ h_{2,1} & h_{2,2} \\ \vdots & \vdots \\ h_{n,1} & h_{n,2} \end{bmatrix}$$

These random extract values, h, from the chi-square distribution are used to transform the **U** matrix. As discussed, we will simulate different degrees of freedom, thus for different values of ν. Therefore we transform matrix **H** to $\hat{\mathbf{H}}$ to include the degrees of freedom ν.

$$\hat{\mathbf{H}} = \begin{bmatrix} \sqrt{\frac{\nu}{h_{1,1}}} & \sqrt{\frac{\nu}{h_{1,2}}} \\ \sqrt{\frac{\nu}{h_{2,1}}} & \sqrt{\frac{\nu}{h_{2,2}}} \\ \vdots & \vdots \\ \sqrt{\frac{\nu}{h_{n,1}}} & \sqrt{\frac{\nu}{h_{n,2}}} \end{bmatrix}$$

After estimating the matrix that is used to transform the normal distribution, we transform the matrix **U** with the Hadamard product, where we multiply each element with the same element of the other matrix. This results in the matrix **T** with the same dimensions as **U** and $\hat{\mathbf{H}}$.

$$\mathbf{T} = \mathbf{U} \circ \hat{\mathbf{H}}$$

The matrix **T** has standardized values, t, these need to be transformed back with its actual mean and standard deviation, which will result in the transformed returns coming from a student t-distribution:

$$\mathbf{St} = \left(\begin{pmatrix} t_{1,1} \\ t_{2,1} \\ \vdots \\ t_{n,1} \end{pmatrix} \times \sigma_{b_1} \right) + \mu_{b_1}$$

After the transformation back, the result is the matrix **St** which represents the transformed returns,

$st_{n,2}$, of the biodiversity risk factors 2 to a student t-distribution in simulation n.

$$\mathbf{St} = \begin{bmatrix} st_{1,1} & st_{1,2} \\ st_{2,1} & st_{2,2} \\ \vdots & \vdots \\ st_{n,1} & st_{n,2} \end{bmatrix}$$

These transformed risk returns replace the biodiversity risk returns in matrix $\hat{\mathbf{F}}$ from the normal distribution. This results in the changed matrix $\mathbf{C}$ which has the returns, $\hat{f}$, of the four risk factors that are extracted from the normal distribution and the returns, st, of the last two columns that are transformed into a student t-distribution.

$$\mathbf{C} = \begin{bmatrix} \hat{f}_{1,1} & \hat{f}_{1,2} & \hat{f}_{1,3} & \hat{f}_{1,4} & st_{1,5} & st_{1,6} \\ \hat{f}_{2,1} & \hat{f}_{2,2} & \hat{f}_{2,3} & \hat{f}_{2,4} & st_{2,5} & st_{2,6} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{f}_{n,1} & \hat{f}_{n,2} & \hat{f}_{n,3} & \hat{f}_{n,4} & st_{n,5} & st_{n,6} \end{bmatrix}$$

After the transformation, the same steps will be followed to calculate the VaR, which is to add the residuals ($\hat{\mathbf{E}}$) and multiply with the weight ($\mathbf{W}$) of each stock. This results in the weekly returns of the portfolio. As discussed we simulate the 99%-VaR over the degrees of freedom, ν, from 3 until 30 degrees. This means that for every degree we estimate the 99%-VaR. The expectation is that the VaR will increase for a lower degree of freedom. The lower degree of freedom results in fatter tails, which could affect the tails of the returns of the portfolio. This could lead to a higher 99%-VaR as the tails of the returns also get fatter. The same will be done for the 99%-ES, which will also be calculated for each degree of freedom.

3.3.2 Simulations without the biodiversity factors

Separate from the previous simulations, we want to investigate the differences between adding biodiversity risk factors to the existing risk factors. Therefore we want to compare the 99%-VaR and 99%-ES with the biodiversity risk factors, with the 99%-VaR and 99%-ES without the biodiversity risk factors. The calculation of the 99%-VaR and 99%-ES without the biodiversity factors consists then only of the risk factors ACWI, HML, SMB, and UMD.

When we calculate both VaR and ES, we will not include the residuals from the regression. These residuals show the difference between the actual returns and the returns we predicted with the regression. When we use fewer factors in the regression when we do not include the biodiversity risk factors, both the betas and the residuals change. This change in betas and residuals might not make a big difference compared to the regression with biodiversity factors. So, we want to compare both regressions without the residuals. This will show us the systemic risk of both regressions. The regression that is used to calculate the VaR and ES with the biodiversity risk factors is then:

$$Rbiodiversity_{i,t} = \alpha_i + \beta_{1,i}RMRF_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}UMD_t + \beta_{5,i}PHY_t + \beta_{6,i}TRA_t \tag{3.7}$$

The regression without the biodiversity risk factors is called 'normal', which is calculated with the following equation:

$$Rnormal_{i,t} = \alpha_i + \beta_{1,i}RMRF_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}UMD_t \tag{3.8}$$

The method of the simulation is the same for the first formula, except that we do not add the residuals ($\hat{\mathbf{E}}$) to the returns. Which results in matrix $\mathbf{P}_{biodiversity}$ that has n simulations. The simulated returns are indicated by $p_{biodiversity}$ of the equity portfolio with the six factors.

$$\mathbf{P}_{biodiversity} = \begin{bmatrix} p_{biodiversity,1} & p_{biodiversity,2} & \cdots & p_{biodiversity,n} \end{bmatrix}$$

The second formula has different betas because the regression is done with only four factors. The matrices $\hat{\mathbf{F}}$ and $\mathbf{X}$ change from $k = 1, ..., 6$ to $k = 1, ..., 4$. The following steps will be the same, except that we do not add the residuals ($\hat{\mathbf{E}}$). Resulting in a matrix $\mathbf{P}_{normal}$, where we have the simulated values p_{normal} of the returns of the equity portfolio, with the four risk factors.

$$\mathbf{P}_{normal} = \begin{bmatrix} p_{normal,1} & p_{normal,2} & \cdots & p_{normal,n} \end{bmatrix}$$

The matrices are used in the same way as $\mathbf{P}$ to calculate the 99%-VaR and 99%-ES as in the previous section. When the differences between both 99%-VaR and 99%-ES are small, there is not much influence from the biodiversity risk factors on the outcome of the VaR and ES of the portfolio. However, when the differences are big, there could be the influence of the biodiversity risk factors on the market risk.

3.4 Conclusion

The market risk of the equity portfolio is calculated using the 99%-VaR and 99%-ES, derived from simulating the portfolio returns. These returns are computed based on weights, betas, risk factors, and residuals. The residuals for each stock are simulated according to their variance obtained from the biodiversity time series regression. Additionally, the same regression provides us with betas for each stock and risk factor, indicating their sensitivity to each factor. The physical and transition risk factors characterize the potential risks associated with both types of risks. Biodiversity risk factors are established by constructing a high-risk minus low-risk portfolio, following the methodology of the HML portfolio by Fama and French (1993). Subsequently, we create physical and transition portfolios, including high and low-risk companies. These steps enable us to assess the market risk of the equity portfolio concerning biodiversity risk and address the research question:

How can market risk be analyzed concerning physical and transition biodiversity risks?

Chapter 4

Data

This research uses a variety of datasets, including the equity portfolio used in this research, the portfolio of ACWI, the risk factors developed by Fama-French, and the exposure data to physical and transition risk. The first section will provide a description of the portfolio of ACWI, the chosen equity portfolio, and the Fama-French factors. Followed by an analysis of the data available to assess exposure to both physical and transition risks. Subsequently, we will delve into the specific biodiversity data applicable to the equity portfolio. This chapter will discuss the research question:

What is the extent and nature of the available data that can be used to assess physical and transition biodiversity risks?

4.1 Portfolio of ACWI

The ACWI is employed as a portfolio in this research to calculate the physical and transition risk factors because it provides a broad perspective of the market. This index comprises 2,920 companies, representing roughly 85% of the globally investable equity universe. It consists of 23 developed and 24 emerging markets, offering a diversified approach to understanding global stock market performance (MSCI, 2024). To follow this index, we extracted the composition from Bloomberg from the iShares Morgan Stanley Capital International (MSCI) ACWI ETF, which follows the MSCI ACWI closely. There are 2,344 stocks extracted from Bloomberg that are in the iShares MSCI ACWI ETF, which is 80.27% of the MSCI index when looking at the number of stocks.

In this research, we use the composition of the iShares MSCI ACWI ETF, as this is available to us. Using the iShares ETF excludes some stocks from the MSCI ACWI index however, the iShares ETF is constructed in such a way that it should match the performance of the MSCI index closely. In this research, we will reference the ACWI, with which we mean the iShares MSCI ACWI ETF. The composition and performance are based on the iShares MSCI ACWI ETF. As of December 30, 2023, the allocation of weights to various countries and sectors is illustrated in Figures 4.1 and 4.2, respectively, which helps in comprehending the construction of the index. The figures show that most of the companies are located in the United States and the biggest percentage is in the Information Technology sector.

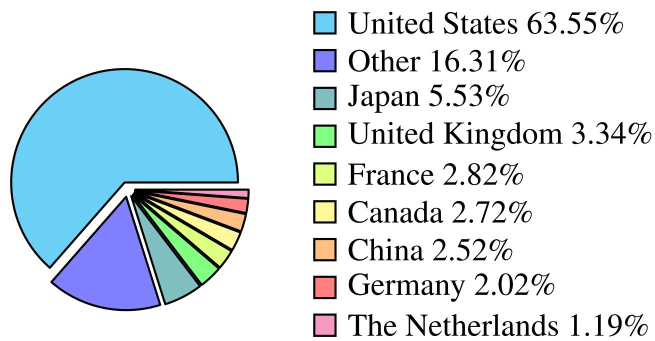


Figure 4.1: Country weights of iShares MSCI ACWI ETF

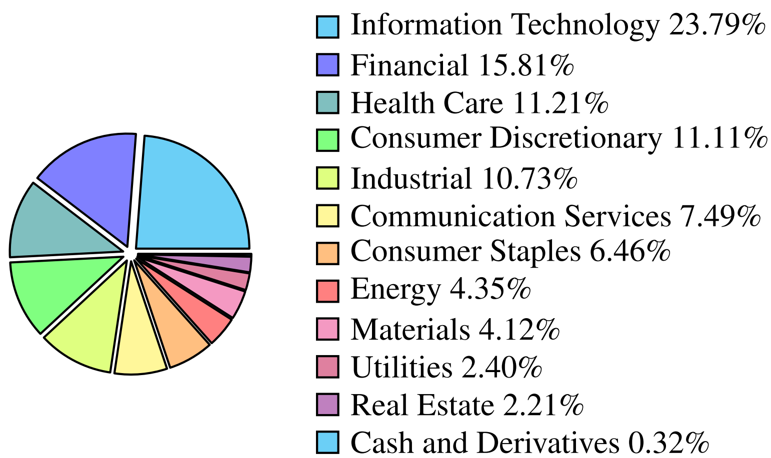


Figure 4.2: Sector weights of the iShares MSCI ACWI ETF

The initial sorting of the portfolios focuses on the size, which is based on the market value, as discussed in section 3.1, which follows the methodology of Huij et al. (2023). The market value is all in USD, sorted on the stocks within our ACWI portfolio[1]. Market value data is available for 2,325 companies. In this research, we decided to exclude the stocks that have no returns available, no weight in the year 2023, and no market value available. This exclusion results in 2,316 stocks that have the information available. The Russian stocks in the index (17 stocks) are also excluded

[1]Extracted from https://www.ishares.com/us/products/239600/ishares-msci-acwi-etf on Dec 29, 2023

from the research, regarding the Ukraine war, a lot of sanctions have been set against Russian stocks, which does not give a representative view. Furthermore, a lot of the Russian stocks do not have biodiversity data at the moment. Moreover, we also excluded six stocks that did not have any MSCI biodiversity data, which we will use as a representation of the biodiversity risk, which are: XTSLA US. MSCI US, COO US, YNDX US, FIVE LI and TCS LI. In the end, 2,293 stocks in the ACWI are included in the research, which have a return, weight, market value, and physical or transition biodiversity data. The iShares ACWI serves as a representative of market behavior, Table 4.1 presents the index's market performance using various indicators, offering insights into its performance.

Table 4.1: Performance of the iShares MSCI ACWI ETF

Indicator[a]	**Performance ACWI**
Total return 2023 (%)	22.22
Total return 2022 (%)	-18.27
Total return 2021 (%)	18.38
Equity Beta (3y)	0.93
Standard deviation (3yrs) (%)	16.68
MSCI ESG Fund Rating (AAA-CCC)	A

[a] These indicators are collected on the fact sheet of Dec 31, 2023.

To derive the biodiversity risk factors, we need to analyze the returns for each stock within the ACWI portfolios. Starting from December 29, 2023, we gather the local price data for the ACWI over the past three years for each stock. Each stock is extracted in its local currency, thereby eliminating the need for currency conversions to US dollars, which could reduce inaccurate price data. This results in weekly prices for the years 2021, 2022, and 2023, totaling 157 weeks. We use percentage returns instead of logarithmic returns because we aim to aggregate the returns at the portfolio level, which is simpler with percentage returns.

$$R_t = \frac{Price_t - Price_{t-1}}{Price_{t-1}} \times 100\% \tag{4.1}$$

Here, t denotes the week, with the dataset's first week representing the final week of 2020, serving as the starting point for return calculations. Consequently, we have 156 weeks of return data for the 2,293 stocks. The return for each made portfolio is computed by summing all returns multiplied by their respective weights in the portfolio. Assuming equal weighting for stocks within each portfolio, we use the formula:

$$R_{Portfolio_t} = \frac{1}{n}\sum_{i=1}^{n} R_{i,t} \tag{4.2}$$

This equation represents the return of the portfolio in week t as the sum of all returns of stock i up to n in week t, divided by the number of stocks n. Some returns are unavailable for specific weeks beginning from the first week of 2021. This is typically due to companies that undergo initial public offerings (IPOs) later within three years. Historical price data becomes available from the time a company goes public, but before that event, no data exists. Since we base our analysis on the portfolio composition as of December 29th, it is possible that companies were not yet public during the preceding 156 weeks. Consequently, prices cannot be extracted from Bloomberg for these periods. Thus, we calculate returns separately for each week to determine its weight. For example, in week 2, there may be 61 returns available, while in week 148, there may be 68 returns available. This implies division by 61 in week 2 and by 68 in week 148. Return calculations for each week are performed for every portfolio.

The biodiversity times series regression that is discussed in section 3.2 is also done for the ACWI as the benchmark, where we only include the stocks with returns for the three years, leaving us with 2,265 stocks. With this time series regression we extract the six betas for each stock, with this information, we can calculate the beta for the portfolio of ACWI. The weights for the ACWI index are also from the 29 December 2023.

4.2 Equity portfolio

The biodiversity time series regression that is discussed in section 3.2, will focus on both physical and transition risk factors and the equities held in the equity portfolio. A global diversified equity portfolio is used in this research. The returns of the equity portfolio are from 2021 until 2023, giving us a 3-year time frame, this matches the time frame of the risk factors. The equity portfolio consists of various stocks and their respective weightings within the portfolio. Resulting in a total investment of 3,054 securities on the 29th of December. Each provided International Securities Identification Number (ISIN) is linked to the corresponding equity, resulting in a total of 1,575 unique equities within the portfolio. This portfolio with unique equities will serve as the basis for conducting the biodiversity time series regression with the physical and transition risk factors. Due to the confidential nature of this information, the precise names

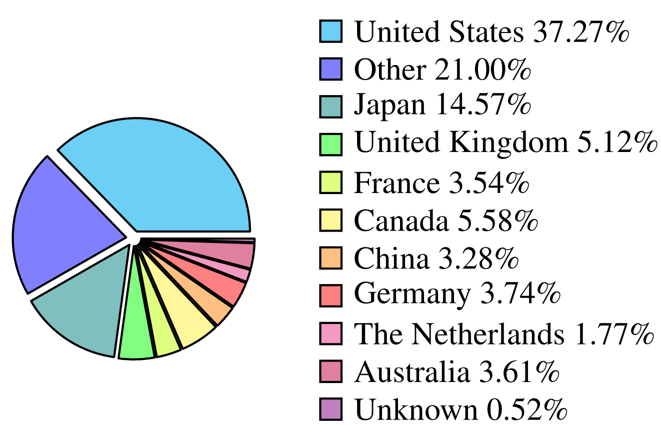


Figure 4.3: Issuer weights of the equity portfolio

of the stocks and their weightings will not be made public in this research. The composition of the equity portfolio is described based on the sector and location composition in Figures 4.4 and 4.3. Just like the ACWI, the equity portfolio consists largely of stocks located in the United States and the highest percentage is in the sector of Information Technology.

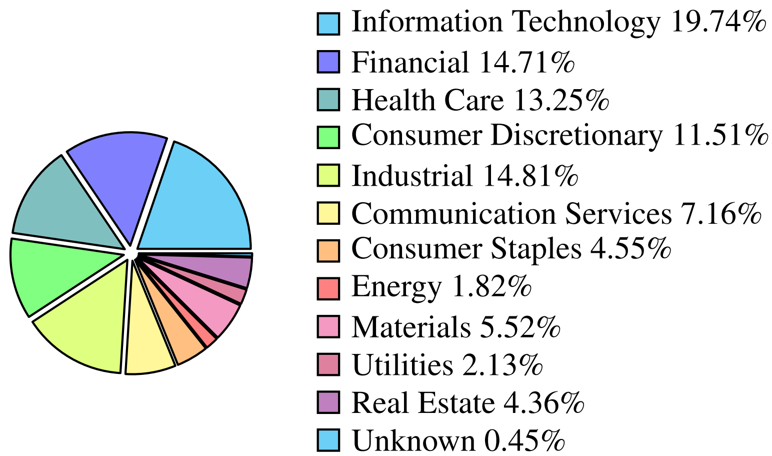


Figure 4.4: Sector weights of the equity portfolio

The focus of the biodiversity time series regression is also on analyzing the biodiversity betas for each stock within the equity portfolio. This examination aims to assess how sensitive these stocks are to changes in the physical and transition risk factors. The equity portfolio consists of 1,575 unique equities, with return data available for 1,523 (96.70%) of them. The stocks with incomplete return data in the three years will be excluded from further analysis. Consequently, our dataset will consist of 1,486 (94.35%) stocks with weekly returns across the three years. Table 4.2 shows the performance of these 1,486 stocks in the equity portfolio. The biodiversity time series regression involves computing the weekly excess returns for each stock. This excess return involves deducting the weekly risk-free rate from the weekly return data. In this research, we follow the same risk-free rate that is used by the Fama-French RMRF factor, which relies on the one-month Treasury bill rate sourced from the Fama-French site.

Indicator	**Equity portfolio**
Weekly mean return	0.242 %
Annual mean return	12.582 %
Weekly standard deviation	2.046 %
Annual standard deviation	14.754 %

Table 4.2: Performance of the equity portfolio

4.3 Fama-French factors

The returns on the four risk factors RMRF, SMB, HML, and UMD can be found on the site of Kenneth French. The return data of the Fama-French factors are collected from the data source by French (2023a). As the equity portfolio and the ACWI have stocks in other markets besides the one from the United States, the developed market factors are chosen in this research. The equity portfolio and ACWI also include emerging markets, this could result in movements of the portfolio that do not exactly move the same as the RMRF factor. At the moment, there are no Fama-French factors that include both developed and emerging markets, due to this we can not incorporate emerging markets in the market factor. Appendix B.1 shows an overview of the countries that are represented in these Fama-French factors for developed markets.

To derive the SMB and HML factors, stocks within a region are categorized into two market capitalization groups and three book-to-market groups after each June. Big stocks represent those within the top 90% of market capitalization for the region, whereas small stocks are those within the bottom 10%. The book-to-market breakpoints for a region are set at the 30th and 70th percentiles of book-to-market for the big stocks within the region, as discussed in French (2023a).

French (2023a) represents the risk factor SMB as the difference in average returns. It is computed as the average of the returns on the three small stock portfolios for the region, subtracted by the average of the returns on the three big stock portfolios.

$$SMB = \frac{1}{3}(\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - \frac{1}{3}(\text{Big Value} + \text{Big Neutral} + \text{Big Growth})$$

Secondly, HML is calculated as the average of the returns for the two high book-to-market portfolios for a region, minus the average of the returns for the two low book-to-market portfolios:

$$HML = \frac{1}{2}(\text{Small Value} + \text{Big Value}) - \frac{1}{2}(\text{Small Growth} + \text{Big Growth}).$$

RMRF measures the market's excess return over the risk-free rate (one-month treasury bill rate). Market return refers to the return on a region's value-weighted market portfolio adjusted by subtracting the one-month T-bill rate. The returns of RMRF, SMB, and HML are daily percentages of change. (French, 2023a)

The momentum factor is calculated in a different dataset. To build the momentum factor, French (2023b) uses six portfolios categorized by size and momentum. These portfolios are created each month by crossing two groups based on market capitalization and three based on prior month returns. The division by size is determined by the median market equity, while the segmentation by past returns uses the 30th and 70th percentiles within the region. The middle portfolio of 40% is then excluded from the momentum factor, leaving us with the highest and lowest percentile. The momentum factor is calculated as the equally weighted average of the returns for the two high past returns portfolios for a region, subtracted by the average of the returns for the two with low past returns portfolios. (French, 2023b):

$$UMD = \frac{1}{2}(\text{Small High} + \text{Big High}) - \frac{1}{2}(\text{Small Low} + \text{Big Low}).$$

All four factors are represented as daily returns. for this research, we use weekly data. Therefore we have to convert these daily returns to weekly returns. Using the formula, where t is the week, which could consist of 5 days, d, or less:

$$R_t = \prod(1 + R_{d,t}) - 1 \tag{4.3}$$

This results in the 156 weekly return data for the years 2021, 2022, and 2023 for each of the risk factors RMRF, SMB, HML, and UMD. Table 4.3 shows the mean return, the 95% confidence interval, and the standard deviation of the weekly and annual returns of each factor.

	RMRF	**SMB**	**HML**	**UMD**
Weekly Mean return	0.105 %	-0.158 %	0.234 %	0.024 %
95% CI	(-0.248, 0.458)	(-0.299, -0.016)	(-0.059, 0.528)	(-0.255, 0.303)
Annual Mean return	5.445 %	-8.209 %	12.189 %	1.252 %
95% CI	(2.898, 7.992)	(-9.230, -7.187)	(10.075, 14.303)	(-0.759, 3.263)
Weekly Standard deviation	2.251 %	0.903 %	1.868 %	1.777 %
Annual Standard deviation	16.230 %	6.520 %	13.472 %	12.816 %

Table 4.3: Performance of the Fama-French risk factors

Table 4.3 shows negative returns for the SMB factor. A positive return would mean that small companies outperform the big companies. In this case, the factor has a negative return, which would mean that the big companies outperform the smaller ones. Looking at the research of Huij et al. (2023), we see differences in the HML and SMB factors. The HML factor is negative and the SMB factor is positive. This can have two reasons, the sample period is different and longer, they take 16 years before 2021. The other reason is that the research of Huij et al. (2023) focuses solely on the United States market, whereas in this research the focus is on developed markets. Looking at the research of Fama and French (1993), all the factors are positive, but the time frame here is from 1963 to 1991.

4.4 Biodiversity data

In this research, one of the goals is to analyze the exposure of individual companies to both physical and transition biodiversity risks to assess the overall market risk. For this purpose, we prioritize obtaining exposure data at the company level, ensuring that the exposure is evaluated specifically for each company, thereby providing insights for each company individually. The biodiversity data used must be objective, meaning it should be factually based and not subject to personal biases. This requirement ensures that the data can be reliably reproduced and remains unaffected by certain viewpoints. To maintain the objectivity and impartiality of the data, the methodology used in data collection and analysis should be transparent. Hence, the methodologies and procedures employed to gather the data must be documented and accessible. In this research, we aim to use data that is specific to individual equities, objective, unbiased, and transparent.

This section discusses the available data on biodiversity. Starting with a broad overview of the public and non-public biodiversity data. Following with more focus on the data that could be useful for the physical and transition risk assessment, and looking into the characteristics of this data. Following the research by the OECD (2023) and further research, a list of companies that could generate data for the assessment of biodiversity risk is set up. In section 2.1.1, databases ENCORE, GLOBIO, BIA-GBS, and IBAT are already discussed, therefore we do not discuss them in this list again. These four databases are used in different studies to assess the biodiversity risk of companies of financial institutions, as Table 2.1 shows. Besides these datasets, we found six other datasets that could be used to assess the biodiversity risks of companies.

1. *Corporate Biodiversity Footprint (CBF)*

   The database CBF is developed by the Iceberg Data Lab, and designed for financial institutions to assess their biodiversity impact. Iceberg Data Lab (2023) uses the indicator MSA, that reflects the degree of degradation that affects the ecosystems by the operations of a company, comparing the current state to their original condition.

2. *Exiobase*

   Exiobase is a global dataset, that facilitates the analysis of environmental impacts associated with the final consumption of product groups on a global scale. (EXIOBASE, 2023)

3. *Ecoinvent*

The database of Ecoinvent looks into environmental impacts associated with products and services, it comprises over 20000 activities of sectors at both global and regional levels as stated by Ecoinvent (2023). The database facilitates users in tracing the environmental impacts of their products throughout the supply chain.

4. *World Wide Fund - Biodiversity Risk Filter (WWF-BRF)*

   The WWF-BRF offers companies and financial institutions a platform, it helps in identifying key areas where interventions are most crucial, as stated by WWF Risk Filter Suite (2023).

5. *MSCI*

   The data of MSCI-ESG entails metrics for investors, particularly in measuring risks and opportunities associated with ESG factors. They have expanded their focus to biodiversity, creating a tool that integrates the ESG data with geospatial data, as stated by MSCI (2023a). The integration allows us to pinpoint risks regarding biodiversity loss.

6. *Biodiversity Impact Assessment Tool (BIAT)*

   The tool of Institutional Shareholder Services (ISS) ESG, called BIAT, assesses the impact of companies on biodiversity with different methodologies, including species richness assessment, species abundance assessment, and supply chain impact assessment. Resulting in two indicators for biodiversity impact, PDF and MSA. (ISS ESG, 2023).

Each of these databases has data to assess the dependence or impact a company has on biodiversity. This data could help to assess how sensitive the companies are to changes in biodiversity. Table 4.4 presents an overview of the 10 datasets that are available to measure biodiversity dependence or impact.

Certain databases are not publicly accessible, which means that their data is unavailable to institutions that have not acquired the necessary licenses. Datasets such as BIA-GBS, CBF, BIAT, and Ecoinvent cannot be used due to the absence of available licenses. These datasets could be of interest, as demonstrated by Svartzman et al. (2021), who show that the BIA-GBS dataset could be used to assess transition risk by measuring the biodiversity footprint of companies. The same applies to the CBF dataset, which calculates the impact of companies on biodiversity and could contribute to assessing transition risk. The BIAT tool, while not used as a dataset in existing literature, provides the PDF and MSA metrics for available companies, offering a method to assess transition risk based on their impact on biodiversity. As these datasets are currently inaccessible, they lay outside the scope of this research. However, when available to financial institutions, they could be valuable for future research in the assessment of physical or transition risk.

Database	**Measure**	**Public data?**
ENCORE	Dependence & Impact score	Public data
BIA-GBS	$MSA.km^2$	Non-public data
GLOBIO	Biodiversity footprint	Public data
CBF	$MSA.km^2$	Non-public data
Exiobase	Environmental impacts	Public data
IBAT	Protected areas & STAR	Public data
Ecoinvent	Environmental impacts	Non-public data
WWF-BRF	Key areas for biodiversity	Public data
MSCI	Companies that may contribute to biodiversity loss	Non-public data
BIAT	MSA & PDF	Non-public data

Table 4.4: Overview of available datasets on biodiversity

Several available datasets rely on geographical information from companies, leading to a geographic data map as an output. However, due to the extensive nature of collecting company-specific geographical data, this aspect falls outside the scope of this research. Consequently, datasets like Exiobase, GLOBIO, IBAT, and WWF-BRF are not used in this study. These datasets would be of interest if the geographical data for all equities in the equity portfolio were available. With these datasets, physical and transition risks could be assessed. Transition risk could be assessed by examining businesses' exposure to protected areas or areas soon to be protected. These companies are exposed to regulatory changes concerning these regions due to their geographical location, as demonstrated by van Toor et al. (2020), Svartzman et al. (2021), Calice et al. (2021), and Bank Negara Malaysia et al. (2022). These papers assess transition risk using datasets from Exiobase and GLOBIO, as well as the database of protected areas found in IBAT. Furthermore, these geographical datasets could provide insights into exposure to physical risk. Protected areas represent areas facing biodiversity loss or requiring protection due to their biodiversity richness. Companies in these areas may depend on this biodiversity richness and could face physical risk due to biodiversity loss. Additionally, companies located in regions experiencing biodiversity loss may be at risk of physical shocks stemming from this loss, thereby exposed to physical risk.

Exploring these datasets could prove valuable for future research if institutions obtain the necessary licenses or collect company-specific geographical data. The datasets of ENCORE and MSCI are available to us. In this research, we need company-specific data to estimate the risk factors. The data of MSCI is company-specific, whereas the ENCORE data is sector-specific. Therefore, we will focus on the biodiversity data of MSCI. Appendix B.2 shows an overview of the methodology of the ENCORE dataset. In the following section, we will provide more detailed insights into the dataset provided by MSCI.

Physical exposure data

As discussed in section 2.1.2, the indicator used to assess the exposure to physical risk is the dependence on ecosystem services. Table 2.2 shows that the literature mostly uses the ENCORE database to look at the physical risk of companies, such as van Toor et al. (2020) and Svartzman et al. (2021). Another database used for physical risk is the Exiobase, used by Svartzman et al. (2021). As discussed before, the Exiobase database is based on geographical data, which we can not use as we have no geographical data for each company in the equity portfolio. The ENCORE database is sector-specific and thus does not give us the information we need.

The MSCI dataset provides interesting data concerning biodiversity indicators. MSCI's data is company-focused, allowing the equity portfolio to be uploaded and connected to the MSCI data. An indicator of physical biodiversity risk can be the geographical location of companies, as the impact of a physical collapse could be more severe in sensitive areas. MSCI offers data on companies and the percentage of their operations situated in highly fragile, moderately fragile, or low-risk areas. This data is summarized in Table 4.5.

MSCI data	**Indicator**	**Explanation**
Estimated percentage of operations located in geographies with highly fragile ecosystems	%	Denotes the portion of the company's assets situated in countries or areas where ecosystems are notably fragile
Estimated percentage of operations located in geographies with moderately fragile ecosystems	%	Denotes the portion of the company's assets situated in countries or areas where ecosystems are somewhat fragile
Percentage of operations in low-risk geographies	%	Denotes the portion of the company's assets situated in countries or areas where ecosystems are not especially fragile

Table 4.5: Overview of MSCI geographical data.

The MSCI data provides a percentage breakdown of a company's operations in highly fragile, moderately fragile, and low-risk ecosystems. The total percentage adds up to 100%. For instance, a company may have 50% of its operations in highly fragile areas, 30% in moderately fragile areas, and 20% in low-risk areas.

Table 4.6 presents an overview of how the ACWI portfolio is classified based on the geographical MSCI data. The table shows the three possible classifications for the geographical dataset, and the values inside the table represent the number of equities in the portfolio falling into the categories of 100%, 0%, or percentages in between. Each row in the table sums up to 2293, representing all the equities in the portfolio. Notably, the data often consists of either 100% or 0%

assigned to a classification. For example, 1974 (86.09%) equities in the portfolio have 0% of their operations located in low-risk ecosystems.

Data	0% of operations	1%-99% of operations	100% of operations
Estimated percentage in highly fragile ecosystems	746 (32.53%)	1205 (52.55%)	342 (14.91%)
Estimated percentage in moderately fragile ecosystems	359 (15.66%)	1373 (59.88%)	561 (24.47%)
Estimated percentage in low-risk ecosystems	1974 (86.09%)	309 (13.48%)	10 (0.44%)

Table 4.6: Overview of how the portfolio is classified based on the geographical MSCI data.

On the company level, the MSCI geographical dataset is suitable for evaluating physical biodiversity risk based on geographical location. The second sorting involves distinguishing between high and low physical risk. In this research, we define high-risk companies as having 100% of their operations in highly fragile ecosystems. Low-risk categorization is approached differently, as there are only a couple of companies with 100% of their operations in low-risk ecosystems. Therefore, we aggregate the percentages to indicate severity, as shown in formula 4.4. High risk, we multiply by three, for medium risk, by two, and for the lowest severity, by one. Companies with a score below 200 are categorized as having low physical risk.

$$\text{Physical score} = 3 \times \text{Percentage high risk} + 2 \times \text{Percentage medium risk} + 1 \times \text{Percentage low risk} \tag{4.4}$$

Transition exposure data

As discussed in section 2.1.3, the indicators used to assess the exposure to transition risk can be the impact on ecosystem services, the exposure to protected areas, or the exposure to certain regulations. Table 2.3 shows that the literature uses very different databases to assess the exposure to transition risk. Due to the different indicators that are defined by the literature, it is not strange that also various datasets are used to assess these different indicators. Calice et al. (2021) and Bank Negara Malaysia et al. (2022) use the database of IBAT to assess the exposure to protected areas. Whereas, van Toor et al. (2020) and Svartzman et al. (2021) use the GLOBIO database to assess the biodiversity footprint of companies, which represents the impact of companies on ecosystem services. Also, the ENCORE database is used to assess the exposure to ecosystems, by Bank Negara Malaysia et al. (2022) and Kedward et al. (2021). The literature shows a lot of different options to use databases to assess transition risk. As previously discussed, there is no geographical data available and we need company-specific data. This results that the data used in the literature is not used in this research.

The MSCI data offers insights for assessing the transition risk indicator in three ways: the impact on ecosystems, the exposure to sensitive areas, and an exposure score for biodiversity & land use. In the previous section, we discussed the geographical data, which could also be relevant for evaluating transition risk due to the exposure to sensitive areas, potentially resulting in regulatory changes related to these areas.

A dataset provided by MSCI that can be used to assess transition risk is the percentage of a company's revenue generated from activities that are minimal, moderate, or substantially involved in disturbance to ecosystems. This data reflects the revenue share generated by a company's activities that impact biodiversity. Table 4.7 presents an overview of MSCI's impact data, which is company-specific. The company data is structured the same as the geographical data, as such that it provides a percentage breakdown for each risk category, indicating the portion of a company's operations that are involved in impacting biodiversity. For instance, company X may have 80% of its operations classified as having a low risk of disturbing areas, 15% with moderate potential disturbances, and 5% with high potential disturbances. These percentages sum up to 100% for each company.

MSCI data	**Indicator**	**Explanation**
Percentage of operations with low risk to disturbance to areas	%	The portion of a company's revenues generated from activities that involve minimal disturbance to marine or land areas.
Estimated percentage of operations with moderate potential disturbances to areas	%	The portion of the company's revenues generated from activities that involve moderate disturbance to marine or land areas.
Estimated percentage of operations with high potential disturbances to areas	%	The portion of a company's revenues generated from activities that involve substantial disturbance to marine or land areas.

Table 4.7: Overview of MSCI - ESG impact data.

Table 4.8 provides an overview of how the portfolio is classified based on the impact dataset. It displays the three possible classifications for the impact data, with values indicating the number of equities in the portfolio falling into the categories of 100%, 0%, or percentages in between. Similar to the geographical data, the impact data often includes either 100% or 0% as percentages, with fewer values in between. For instance, 2059 (89.90%) equities in the portfolio have 0% of their operations categorized as having a high potential to disturb areas. On the other hand, 1408 (61.04%) have 100% of their operations in low-risk impact on the areas. This table shows that there are not a lot of companies with different percentages than 0% or 100%, which makes it difficult to sort the companies based on this dataset, because these companies will often have the same scores.

Data	0% of operations	1%-99% of operations	100% of operations
Estimated percentage with high potential disturbances to areas	2059 (89.90%)	166 (7.24%)	68 (2.97%)
Estimated percentage with moderate potential disturbances to areas	1742 (75.97%)	455 (19.84%)	96 (4.19%)
Percentage with low risk to disturbance to areas	227 (9.90%)	658 (28.70%)	1408 (61.04%)

Table 4.8: Overview of how the portfolio is classified based on the impact of MSCI data.

Another dataset provided by MSCI that can be valuable for assessing transition risk is the Biodiversity & Land Use exposure score. This score, ranging from 0 to 10, is based on a combination of business exposure and geographic exposure scores.

1. **The business exposure score** is calculated as the average of the business impact score and the controversies score.

   - **The business impact score** is determined through the impacts associated with specific business activities. Nine distinct business impacts related to changes in biodiversity and ecosystems are considered by MSCI, and each impact is assigned a value of 0 or 1 for each business activity, where 1 signifies the presence of the impact. The cumulative number of impacts relevant to each activity is counted to compute the impact score.
   - **The controversies score** is determined based on the proportion of companies engaged in biodiversity controversies assessed as moderate to very severe, relative to all companies sharing the same business activities.

2. **The geographic exposure score** is determined by averaging the annual forest area loss score and the score based on the number of threatened species in a country. The annual forest area loss is calculated based on the average annual forest loss per country over 5 years.

The Biodiversity & Land Use exposure score is calculated using the following formula by MSCI (2023b):

$$EXP_{BIO,i} = BUS_{BIO,i}(1 + 0.1(GEO_{BIO,i} - 5)) \tag{4.5}$$

Where $EXP_{BIO,i}$ is the Biodiversity & Land Use exposure score of the company i. $BUS_{BIO,i}$ is the business exposure score, and $GEO_{BIO,i}$ is the geographic exposure score for company i. (MSCI, 2023b)

The Biodiversity & Land Use exposure score can be a valuable indicator for assessing transition risk. The business exposure score reflects the risks associated with regulations or customer preferences related to impacts on biodiversity and ecosystems, while the geographic exposure score indicates the risk of regulations regarding sensitive areas. Figure 4.5 presents the distribution of equities in the ACWI for different exposure scores, showing that many equities have relatively low scores, mainly below the score of 2.

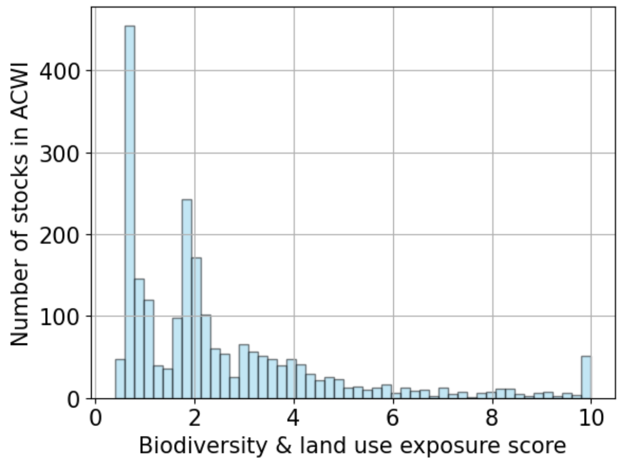


Figure 4.5: Frequency of the biodiversity & land use exposure score

MSCI's biodiversity & land use exposure score is used to assess the transition biodiversity risk, offering an indicator of risk based on the company's impact on biodiversity. The high-risk companies are defined in this research as having a score of 5 or higher, while low-risk companies are defined with a score of 0.6 or lower.

As discussed, we aim to use data that is specific to individual equities, objective, unbiased, and transparent. However, there are concerns regarding the objectivity, impartiality, and transparency of MSCI's data. MSCI has not provided clear information on their data collection methods, especially concerning how they calculate the percentages of operations in highly fragile environments or the percentage of operations that have moderate potential to disturb the areas. This lack of transparency raises questions about the objectivity and impartiality of MSCI's biodiversity-related data.

Berg et al. (2022) talk about various providers of ESG data and biodiversity data. These biodiversity datasets differ from those previously discussed but include the MSCI dataset we talked about earlier. The mentioned providers include Sustainalytics, S&P Global, Moody's, Refinitiv, KLD, and MSCI. Berg et al. (2022) reveal that there is little correlation between the datasets regarding biodiversity. For instance, the datasets from MSCI and Refinitiv show a correlation of 0.2 in biodiversity scores, indicating frequent mismatches in scoring equities on biodiversity. This lack of correlation suggests that using different datasets may result in different compositions when constructing portfolios based on biodiversity risk, potentially leading to varying risk factors and premiums compared to those in this research. Another issue is the difficulty in assessing the reliability and objectivity of these datasets due to their lack of correlation. This can potentially lead to "greenwashing," as described by Investopedia (2023) as *'Greenwashing is the process of conveying a false impression or misleading information about how a company's products are environmentally sound.'*. The lack of correlation among the data implies that some of the biodiversity may be misleading since different providers assess equities differently. The datasets of Refinitiv are also available to us, when looking into the datasets three indicators were found. Representing the share of investments operating in or near biodiversity-sensitive areas, the share of investments contributing to the decline of endangered species, and the proportion of non-vegetated surface area relative to the total surface area. The three indicators only have the score of true or false, which is difficult to use to create the high and low biodiversity risk portfolios.

Nevertheless, MSCI is one of the few sources available to us that offers biodiversity data. Consequently, we will proceed with using this data, while acknowledging that it may not fully meet the criteria for objectivity, impartiality, and transparency.

4.5 Conclusion

The chapter discusses the datasets used in the methodology, including the equity portfolio, the ACWI portfolio, and the Fama-French factors. The latter part focuses on current biodiversity data availability. In this study, our goal is to use data specific to individual companies that is objective, unbiased, and transparent. During the exploration of various datasets, we excluded those inaccessible due to licensing and those dependent on geographical information. The MSCI dataset provided company-specific information. Physical risk is defined by the percentage breakdown of a company's operations in highly fragile, moderately fragile, and low-risk ecosystems. Transition risk is defined by the Biodiversity & Land Use exposure score, representing risks associated with regulations or customer preferences impacting biodiversity and ecosystems, while the geographic exposure score indicates the risk of regulations concerning sensitive areas.

The lack of transparency in MSCI's biodiversity-related data raises concerns about its objectivity and impartiality. The absence of correlation between different providers of biodiversity data implies that different datasets may give varying compositions when constructing portfolios based on biodiversity risk, potentially resulting in different risk factors and premiums compared to those in this research. This discrepancy in correlation could indicate "greenwashing", where companies present a misleadingly positive impression of their environmental impact.

In conclusion, the chapter discusses the extent and nature of available datasets for assessing physical and transition risk, leading to the selection of MSCI datasets for this research. We also address the risks associated with this choice, such as the potential for greenwashing. This addresses the research question:

What is the extent and nature of available data that can be used to assess physical and transition biodiversity risks?

Chapter 5

Results

This chapter details the results of each step in the framework. Initially, we identify the physical and transition risk factors and determine if there is a risk premium associated with each. Then, we use this information to calculate betas through a times series regression analysis, showing how sensitive the equity portfolio is to these biodiversity risk factors. These findings assist in simulating the potential losses of the equity portfolio, helping us to estimate its VaR and ES. All the outcomes of each step are discussed in this chapter. The portfolio's sensitivity to physical and transition risks, as well as the estimation of VaR and ES, reflect the impact of these risks on market risk and provide answers to the two research questions.

1. *How is an equity portfolio exposed to physical and transition risks associated with biodiversity?*
2. *What is the impact of the biodiversity risks on the market risk of an equity portfolio, and what are the implications of these risks?*

5.1 Biodiversity risk factor

In this section, we estimate both physical and transition risk factors, PHY and TRA. This involves the method of the construction of a HML portfolio following the Fama-French model, as discussed in Section 3.1. As outlined in the methodology, a double-sorting process is used. Initially, we sort the companies within the ACWI based on their size, which is represented as the market value.

Sorting the stocks by size can be executed in various ways, one approach being to make the split between big and small companies by the median. The median market value among these stocks is \$2,744,118.36. This results in two distinct portfolios: one consisting of large companies, 1,147 companies, which consist of 91.22% of the weight in the index. On the other hand, the small companies consist of 1,146 companies, comprising 7.97% of the index. Table 5.1 provides further insights into the market value distribution within the ACWI portfolio.

	Market value
Median	$ 2 744 118.36
Average	$ 8 233 117.92
Highest market value	$ 850 489 530.67
Smallest market value	$ 3.39

Table 5.1: Market value of iShares MSCI ACWI ETF index

An alternative method for sorting stocks by size involves selecting a percentile of both the largest and smallest companies. In this research, a 10% percentile as Fama-French does in French (2023a), will give two portfolios of each 229 stocks. The physical and transition company data is created such that there are a lot of companies with the same score, making it difficult to create high and low-risk portfolios from the small portfolio of 229 stocks. It leads to a big difference between the sizes of the four portfolios for both physical and transition risk. In this study, we therefore decide on the 20% percentile, resulting in two portfolios, each comprising 459 stocks.

In this research, we have decided to utilize a percentile rather than the median. This decision is made to create more concentrated portfolios that consist of the largest and smallest companies. By using this approach, it is anticipated that the correlation with size characteristics will be reduced, as they are partly removed from the composition of the portfolios. The correlation between the risk factors will be discussed at the end of this section.

5.1.1 Physical risk factor

In this subsection, we will be estimating the physical risk factor using Equation 3.1. To accomplish this, we need to create four portfolios: B/HP, S/HP, B/LP, and S/LP. The sorting between large and small companies has already been conducted as explained earlier. We use the geographical data from MSCI for the second sorting, which represents the risk companies face regarding physical biodiversity risk, as discussed in section 4.4.

Beginning with the portfolio of large companies, geographical information was available for 459 companies (100%). The second sorting involves distinguishing between high and low physical risk. In this research, we define high-risk companies as having 100% of their operations in highly fragile ecosystems, resulting in 60 companies identified as high-risk within the portfolio of large companies. Low-risk categorization is approached differently, using Equation 4.4. Companies with a score below 200 are categorized as having low physical risk, resulting in a portfolio of 34 companies. For the portfolio of small companies, geographical information was available for 459 companies (100%). Following the same sorting approach, we identify 91 companies with high risk and 30 companies with low risk within the portfolio of small companies. Table 5.2 presents an overview of these portfolios.

	High risk	**Low risk**
Large companies	60	34
Small companies	91	30

Table 5.2: Amount of companies in each physical portfolio

Though there are differences in the number of stocks within each portfolio, the large quantity of stocks within each ensures diversification. Additionally, each portfolio is equally weighted, so variations in the number of stocks do not impact returns, as each stock's return contributes equally to the overall portfolio return. However, changes in the composition of a portfolio, resulting from more or fewer stocks, can influence its returns. While these portfolios are chosen for this research, different outcomes for portfolio composition may arise when using alternative data to represent biodiversity risk. Currently, we have created the composition of the four portfolios: B/HP, S/HP, B/LP, and S/LP. To derive the physical risk factor, we need to analyze the returns for each stock within these portfolios, which results from the returns calculated from the portfolio of ACWI in Section 4.1. Table 5.3 provides for each portfolio, the mean return, the 95% confidence interval, and the standard deviation for the weekly and annual return.

Portfolio	**Weight in Index (%)**	**Mean return (%)**		**Standard deviation (%)**	
		Weekly	Annual	Weekly	Annual
Big/High (B/HP)	5.557	0.234 (-0.107, 0.575)	12.155 (9.696, 14.614)	2.173	15.669
Small/High (S/HP)	0.291	0.057 (-0.391, 0.504)	2.940 (-2.820, 3.635)	2.852	20.568
Big/Low (B/LP)	3.530	0.291 (-0.043, 0.625)	15.130 (12.719, 4.509)	2.130	15.362
Small/Low(S/LP)	0.119	0.258 (0.007, 0.509)	13.423 (11.611, 15.234)	1.601	11.542

Table 5.3: Physical portfolios return information

The final step involves estimating the PHY factor using Equation 3.1 with the four portfolios created. Initially, for each week, we aggregate the returns of portfolios B/HP and S/HP, dividing the sum by two. Similarly, we perform this process for the returns of B/LP and S/LP, resulting in weekly returns for two portfolios: the high and low physical risk portfolios.

While assessing the high and low physical risk portfolios, we are also interested in understanding their sector compositions. Table 5.4 displays the composition of both high and low-risk portfolios. Notably, sectors such as Financials, Industrial, and Consumer Discretionary are prominently represented in both portfolios. However, each sector is present in both portfolios, except for the Healthcare sector in the low-risk. Given that physical risk is determined by the percentage of operations in highly, moderately, or low-fragile ecosystems, it is not reliant on the nature of production or services. Instead, it depends on the geographical locations of the companies, presenting it as less sector-specific. Consequently, each sector is almost represented in both portfolios.

Sector	**High-risk portfolio (%)**	**Low-risk portfolio (%)**
Communication Services	9	5
Consumer Discretionary	13	16
Consumer Staples	11	3
Energy	5	5
Financials	17	25
Health Care	7	0
Industrials	9	22
Information Technology	3	3
Materials	9	11
Real Estate	9	6
Utilities	8	5

Table 5.4: Sector composition of the physical portfolios

Therefore, we also investigated the locations of both portfolios, as represented in Table C.1 in Appendix C. The location of each company is based on the domicile of the issuer, often their headquarters. It does not indicate where the business and operations of each company are located. The table illustrates that high-risk companies are primarily situated in the United States and China, possibly due to the concentration of large companies in these countries. Large companies conduct business and operations in various locations worldwide, which may cause the risk associated with a significant portion of their activities being in highly fragile ecosystems. Conversely, the low-risk portfolio exhibits substantial geographic diversification, predominantly across developed countries. These companies typically conduct their businesses and operations within their respective countries, particularly in European nations, potentially resulting in lower physical risk. European countries tend to have less fragile ecosystems compared to regions like the Amazon or coral reefs, reducing the overall risk exposure.

Now that we have made both the high and low-physical risk portfolios and estimated their weekly returns, deriving the PHY is simply a matter of subtracting the return of the low-risk portfolio from that of the high-risk portfolio. This results in the PHY with a weekly return. Table 5.5 presents statistical information regarding both the high-risk and low-risk portfolios, as well as the PHY. Figure 5.1 illustrates the cumulative return of the PHY over the three years. The cumulative returns offer a straightforward way to understand the portfolio's performance over the three years. Additionally, it provides a picture of the overall growth or decline of the investment. The correlation of the physical factor with other risk factors will be discussed in section 5.1.3.

	μ (weekly %)		μ (annual %)		Standard deviation (%)	
	Mean	95% CI	Mean	95% CI	Weekly	Annual
High-risk portfolio	0.145	(-0.188, 0.478)	7.547	(5.144, 9.951)	2.124	15.317
Low-risk portfolio	0.275	(0.002, 0.547)	14.276	(12.310, 16.243)	1.738	12.531
PHY	-0.129	(-0.364, 0.105)	-6.729	(-8.421, -5.037)	1.495	10.780

Table 5.5: Physical risk factor return information

The statistical analysis reveals a negative weekly and annual mean return for physical risk. Consequently, there exists a negative risk premium concerning physical biodiversity. This implies that companies with higher physical risk do not require a higher risk premium. Figure 5.1 illustrates the performance of the PHY, which has a decreasing return over the three years. A negative premium regarding physical risk can occur because of different reasons. First of all, normally risk premiums are calculated over a longer period, as we chose three years, it is possible that we did not capture a positive risk premium due to the small period. Another reason can be that the physical risk is not priced in, and investors do not yet care about the physical risk of biodiversity loss. On the other hand, it also can be because of the biodiversity data which is used for the physical risk. It could be that it does not yet capture the physical risk the companies entail.

5.1.2 Transition risk factor

The same method is applied to the transition risk factor, using Equation 3.2. The four portfolios B/HT, S/HT, B/LT, and S/LT need to be created. The sorting between large and small companies has already been addressed as previously explained. The MSCI Biodiversity & Land Use exposure score is used for the second sorting, which represents the risk companies face regarding transition biodiversity risk, scores range from 10 to 0, as discussed in section 4.4.

Beginning with the portfolio of large companies, which entails 459 companies, data on exposure scores was available for 459 large companies (100%). The high-risk companies are defined in

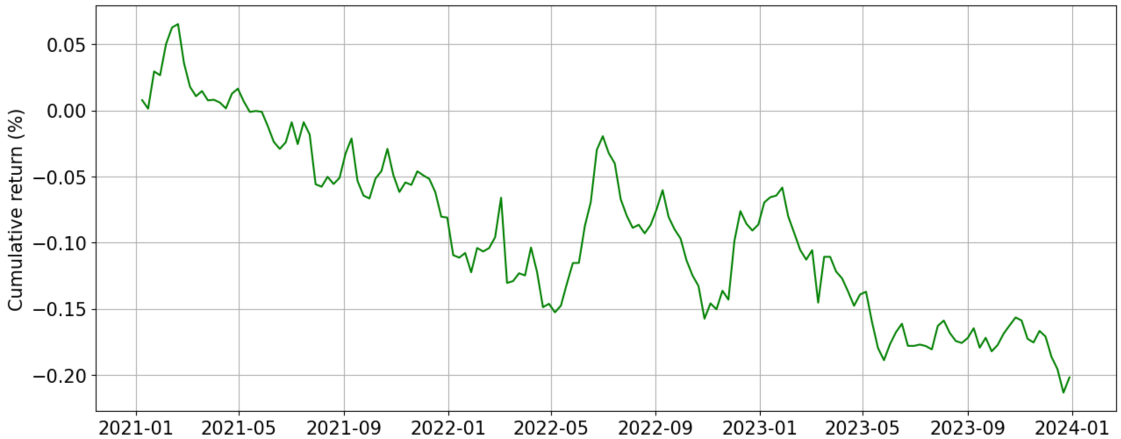


Figure 5.1: Performance of PHY

this research as having a score of 5 or higher, which are 48 large companies, while low-risk companies are defined with a score of 0.6 or lower, including 65 large companies. The same approach is applied to the small companies portfolio, including 459 companies (100%) for which data was available. The high-risk portfolio consists of 72 companies, while the low-risk portfolio includes 33 companies. As mentioned with the physical portfolios, there are variations in portfolio sizes. However, given their size, they still have a diversified nature because of this, they are expected to capture the transition risk. Table 5.6 provides an overview of the number of stocks in each portfolio.

	High risk	**Low risk**
Large companies	48	65
Small companies	72	33

Table 5.6: Amount of companies in each transition portfolio

Now that we have created the composition of the four portfolios, B/HT, S/HT, B/LT, and S/LT to derive the TRA, we need to analyze the returns for each of the stocks. Table 5.7 provides an overview of the information for each portfolio.

The final step involves estimating the TRA using Equation 3.2 with the four portfolios created. Initially, for each week, we aggregate the return of portfolios B/HT and S/HT, dividing the sum by two. Similarly, we perform this process for the returns of B/LT and S/LT, resulting in weekly returns for two portfolios: the high and low transition risk portfolios.

Table 5.8 displays the sector composition of the transition portfolios. In contrast to the physical portfolio, the transition portfolios are heavily represented in certain sectors. The high-risk

Portfolio	**Weight in Index (%)**	**Mean return (%)**		**Standard deviation (%)**	
		Weekly	Annual	Weekly	Annual
Big/High (B/HT)	5.360	0.380 (-0.029, 0.789)	19.776 (16.826, 22.726)	2.607	18.798
Small/High (S/HT)	0.248	0.194 (-0.111, 0.500)	10.106 (7.903, 12.309)	1.947	14.038
Big/Low (B/LT)	8.857	0.224 (-0.234, 0.681)	11.634 (8.335, 14.933)	2.915	21.023
Small/Low(S/LT)	0.107	0.114 (-0.164, 0.391)	5.913 (3.914, 7.913)	1.767	12.740

Table 5.7: Transition portfolios return information

portfolio mainly consists of the Materials and Energy sectors, accounting for more than 60% of the portfolio combined. On the other hand, the low-risk portfolio is mainly represented by the Information Technology, Financials, and Communication Services sectors. This sector concentration is not unexpected, as high-risk transition stocks have a more significant impact on biodiversity. Sectors such as Materials, Energy, and Industrials typically have considerable biodiversity impacts. The low-risk sectors are often not directly linked to high biodiversity impact, as these companies mainly provide digital services rather than producing physical products.

Sector	**High-risk portfolio (%)**	**Low-risk portfolio (%)**
Communication Services	0	20
Consumer Discretionary	0	6
Consumer Staples	10	0
Energy	28	0
Financials	0	33
Health Care	0	2
Industrials	18	6
Information Technology	2	24
Materials	36	0
Real Estate	0	8
Utilities	7	0

Table 5.8: Sector composition of the transition portfolios

Table C.2 in Appendix C displays the composition of the locations for both transition portfolios. Both portfolios show diversification across various countries. However, a significant proportion of companies in both portfolios are situated in the United States. This can be based on the ACWI Index's substantial investment in United-States-based companies.

Having created both the high and low-transition risk portfolios and estimated their weekly returns, deriving the TRA now involves simply subtracting the return of the low-risk portfolio from that of the high-risk portfolio. This gives the TRA a weekly return. Table 5.9 provides statistical information about both the high-risk and low-risk portfolios, as well as the TRA. Figure 5.2 illustrates the cumulative returns over three years.

	μ (weekly %)		μ (annual %)		Standard deviation (%)	
	Mean	95% CI	Mean	95% CI	Weekly	Annual
High-risk portfolio	0.287	(0.012, 0.563)	14.941	(12.955, 16.927)	1.755	12.658
Low-risk portfolio	0.169	(-0.169, 0.506)	8.774	(6.339, 11.208)	2.152	15.516
TRA	0.119	(-0.233, 0.471)	6.167	(3.629, 8.706)	2.243	16.176

Table 5.9: Transition risk factor return information

The statistical data presented in Table 5.9 indicates a positive weekly and annual mean return for transition risk. Consequently, there exists a positive risk premium concerning transition biodiversity. This implies that companies with higher transition risk require a higher risk premium. Figure 5.2 demonstrates a clear positive performance over the three-year time frame.

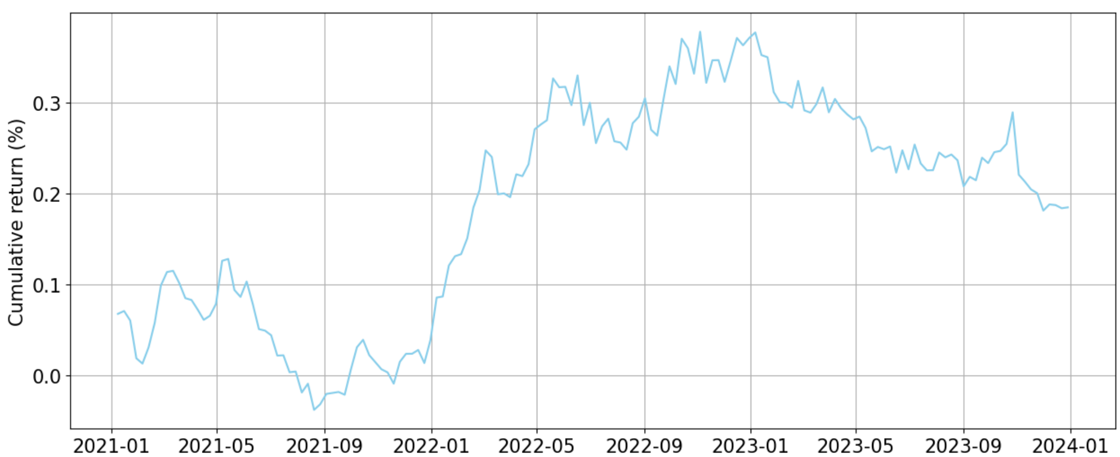


Figure 5.2: Performance of TRA

5.1.3 Correlation

Table 5.10 indicates the correlation between the six risk factors, based on their weekly returns. Figure 5.3 shows the cumulative returns of each risk factor. Cumulative returns provide a simple way to understand how the risk factor has performed over the three years. Moreover, the graph gives a snapshot of whether the risk factor has grown or declined overall.

	PHY	**TRA**	**RMRF**	**SMB**	**HML**	**UMD**
PHY	1.000					
TRA	0.056	1.000				
RMRF	0.072	-0.553	1.000			
SMB	0.001	0.007	0.079	1.000		
HML	-0.239	0.529	-0.346	-0.118	1.000	
UMD	0.028	0.280	-0.224	-0.026	0.205	1.000

Table 5.10: Correlations between the risk factors

The PHY presents a modest positive correlation with the market factor and a modest negative correlation with the value factor (HML). Moreover, it demonstrates minimal correlation with the transition risk factor, size factor (SMB), and momentum factor.

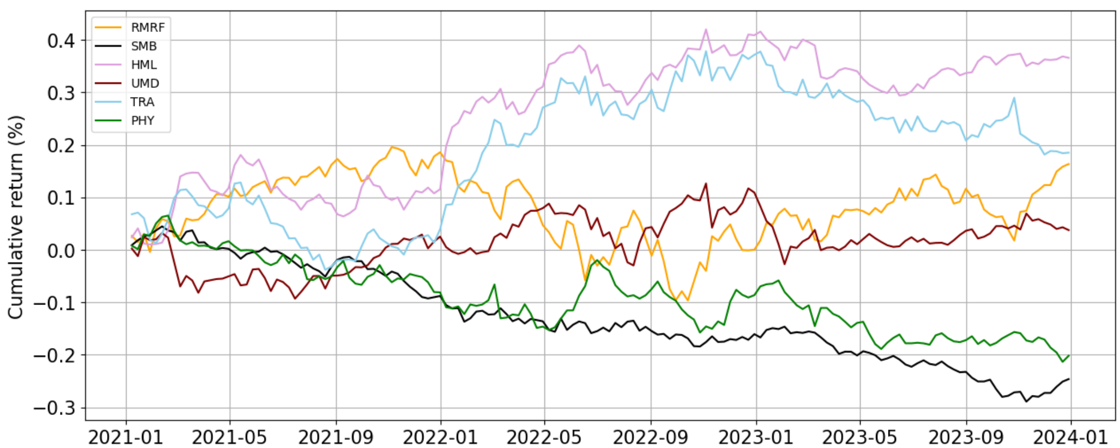


Figure 5.3: Performance of all the risk factors

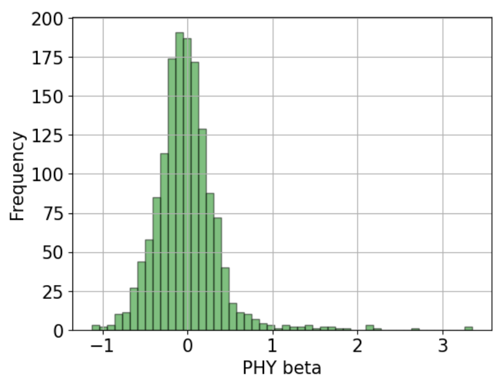
On the other hand, the TRA displays a strong correlation with the value factor and the market factor. The relationship between TRA and HML is depicted in Figure 5.3, illustrating the simultaneous movement between the HML and TRA lines. The strong correlation could imply that the transition risk factor does not capture the transition risk but rather captures the value factor. However, a correlation of 0.529 is relatively high, but still far enough from 1 to assume that the TRA captures the transition risk. One reason transition risk and value risk might be correlated is their shared proportion of the same sectors. As shown in Table 5.8, high-risk transition companies are primarily concentrated in sectors like Energy, Industrials, and Materials. The value factor assesses the book-to-market ratio. The value stocks are those with high book-to-market ratios, which are often large, established companies. In contrast, growth companies, with low book-to-market ratios, are typically smaller or mid-sized entities with growth potential. Sectors with high transition risk, such as Energy, Industrials, and Materials, often overlap with value stocks, while low-transition sectors like Information Technology and Consumer Services often align with growth companies. This potential overlap could explain the relatively high correlation between the factors.

5.2 Biodiversity beta

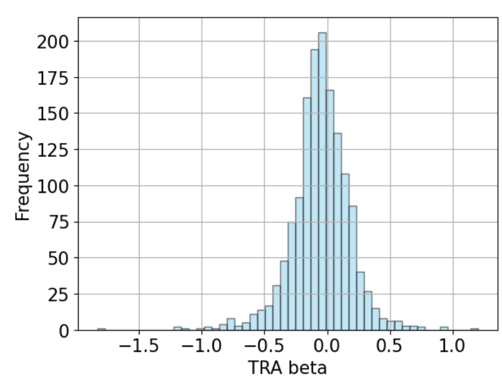
In this section, we will estimate the physical and transition betas using Equation 3.3, as outlined in Section 3.2. Applying the Ordinary Least Squares (OLS) method, which conducts multiple linear time series regressions. The equity portfolio consists of 1,486 stocks which are used in this time series regression, as discussed in 4.2. Through the OLS regression, we estimate the betas for each risk factor related to every stock. The time series regression outcome has among other results the six betas, an alpha, p-values, and a residual for each stock. The objective of the betas is to capture the exposure to biodiversity risk factors, indicating the sensitivity to these factors. A lower beta for these factors suggests lower exposure of the stock to the biodiversity risk factor.

5.2.1 Physical and transition beta

We extracted the six betas for each stock, which is a list of 1,486 betas for each risk factor. Figures 5.4a and 5.4b present the betas of the physical and transition risk factors, where the mean of the PHY is -0.016. The mean of the TRA lies at -0.054, both close to zero. In the figures, it can be seen that there are some outliers. However, most of the betas lie around zero. The other betas of RMRF, SMB, HML, and UMD are represented in Appendix D.1.



(a) Frequency distribution of the physical beta



(b) Frequency distribution of the transition beta

Figure 5.4: The frequency distributions for both biodiversity risk factors

Table 5.11 shows the portfolio beta for all six risk factors. The beta of the PHY factor is positive, this means that there is some exposure in the equity portfolio to the physical risk factor.

On the other hand, the beta of the TRA is negative, which means when looking at exposure the equity portfolio has a low exposure to the transition risk factors. However, both are very small, meaning that there is not much exposure to these risk factors.

	RMRF	SMB	HML	UMD	**PHY**	**TRA**
Portfolio beta 2023	0.775	0.111	-0.131	-0.027	0.009	-0.078

Table 5.11: Portfolio betas

Table 5.11 shows the six different betas of the portfolio. Notably, the market beta (RMRF) is not equal to one. In theory, we would expect the market beta to be close to one in a well-diversified portfolio, as this moves with the market performance. Another way to ensure that the RMRF factor moves with the equity portfolio is to include the ACWI as the market factor, instead of the Fama-French market factor. The ACWI includes emerging markets and therefore could be a better representative of the market. However, when changing the market factor to the ACWI, it is important to note that the other Fama-French factors are still extracted from only developed markets. In this research, we decided to change the market factor to the ACWI, as this gives a better representation of the market. Changing the other factors to include emerging markets lies outside the scope of this research. The ACWI with local prices is extracted from Bloomberg because the prices of the returns of the equity portfolio are also in local prices. As the last step, we subtract the risk-free rate from the index, the same as we use for the equity portfolio.

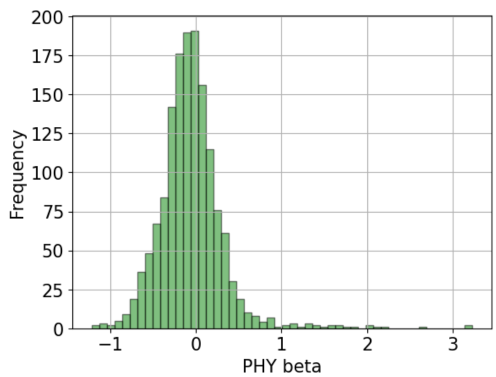
Changing the market factor to the ACWI results in changing correlations and performance of the market factor, these changes are represented in Appendix D.2. The changing market factor also results in different results for the regression, which are depicted in Figures 5.5a and 5.5b. The changed beta results of the other risk factors are represented in D.2.

Table 5.12 shows the aggregated betas of the equity portfolio, which shows an increased beta of the market factor. Consequently, the ACWI is a better fit for the market factor than the Fama-French market factor. Another interesting change is that the physical beta becomes a negative value. This could mean that the equity portfolio has less exposure to the physical risk factor.

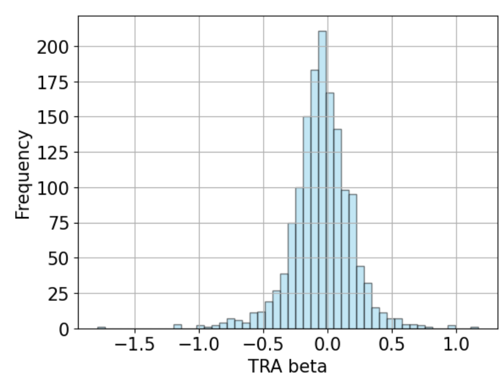
	ACWI	SMB	HML	UMD	**PHY**	**TRA**
Portfolio beta 2023	0.889	0.252	-0.112	-0.041	-0.033	-0.072

Table 5.12: Portfolio beta with the ACWI

Table 5.13 shows the statistics of the biodiversity betas with the times series regression with



(a) Frequency distribution of the physical beta with the ACWI



(b) Frequency distribution of the transition beta with the ACWI

Figure 5.5: The frequency distributions for both biodiversity risk factors with the ACWI

the ACWI. As can be seen in Figure 5.5a the maximum value of the physical betas is 3.229, which is relatively high against the transition betas. The skewness shows what can be seen in the graphs, that the physical beta is skewed to the right, giving us a positive value. On the other hand, the transition beta is skewed to the left and has a negative value. The value of the kurtosis for the physical betas is positive and relatively high. Meaning that the values lie away from normal distribution, with fatter tails. Both the median and mean of the biodiversity betas are negative, meaning that most of the betas have a negative exposure to the biodiversity risk factors.

Statistic	**Beta of PHY**	**Beta of TRA**
Maximum	3.229	1.174
75% percentile	0.110	0.082
Median	-0.085	-0.046
Mean	-0.058	-0.047
25% percentile	-0.262	-0.164
Minimum	-1.218	-1.790
Skewness	2.057	-0.512
Kurtosis	12.357	4.597

Table 5.13: Statistics of the Betas of PHY and TRA

Model validation

The regression with the ACWI will be further investigated. As we look at the significance of the physical and transition betas in the regressions there are a lot of stocks with a high p-value. Table 5.14 shows that a low percentage of the stocks have a statistically significant physical or transition beta. Considering a significance level of 0.05, it indicates that less than 10% of the stocks have a significant relationship between the transition factor and its beta. This suggests that we cannot claim with certainty that the observed relationship between the transition factor and its beta is statistically significant and not purely due to chance, for the stocks with a higher p-value than 0.05. However, biodiversity is a new subject for investors, which could mean that at the moment they do not always take both risk factors into account. This suggests that the low significance of both risk factors is understandable, given that they represent the risk of biodiversity loss.

	p-value		
	0.1	**0.05**	0.01
ACWI betas significant	1367 (91.99%)	1340 (90.17%)	1230 (82.77%)
SMB betas significant	690 (46.43%)	526 (35.40%)	296 (19.92%)
HML betas significant	794 (53.43%)	689 (46.37%)	502 (33.78%)
UMD betas significant	381 (25.64%)	257 (17.29%)	116 (7.81%)
PHY betas significant	435 (29.27%)	323 (21.74%)	172 (11.57%)
TRA betas significant	243 (16.35%)	140 (9.42%)	39 (2.62%)

Table 5.14: Regression significance

The regression also gives the value of the R-squared and adjusted R-squared, which represents to which extent the model explains the variance. In this case, it represents to what extent the returns of the risk factors explain the variance of the returns of each stock. The biodiversity regression gives each company a value for the R-squared and adjusted R-squared. Table 5.15 shows the various values of the regression, as we could not show 1,486 different values, the table shows the distribution of the values. The majority of the R-squared values lie below the value of 0.3. This means that for these companies, less than 30% of the total return variance is explained by the risk factors. This shows that a large part of the returns are not explained by the risk factors, which could mean that we missed some relevant variables that could explain the returns of each company.

Statistic	**R-squared**	**Adj. R-squared**
Maximum	0.680	0.667
75% percentile	0.397	0.373
Median	0.281	0.252
Mean	0.288	0.260
25% percentile	0.161	0.127
Minimum	0.016	-0.023

Table 5.15: Statistics of the R-squared and the adjusted R-squared

The biodiversity times series regression is at the moment only done with in-sample data. The validation of the model should also be done with out-of-sample data. The out-of-sample test could be used to assess if the time series regression is a good fit for the used data. Tashman (2000) discusses that the effectiveness of forecasting methods is best evaluated through out-of-sample tests rather than relying solely on the goodness of fit of the in-sample data, and thus past data. Firstly, in-sample errors for a given forecasting method are likely to underestimate forecasting errors since method selection and estimation are tailored to historical data, which may not fully represent the future. Secondly, methods chosen solely based on in-sample fit may not accurately predict post-sample data.

Sector comparison

Now we have a view of the beta of the equity portfolio. Besides that, we are interested in the weighted physical and transition beta for each sector in the portfolio. Figure 4.4 represents the composition of the equity portfolio regarding the sectors. Three stocks did not have one of the official eleven sectors from GICS, because of this we could not extract them from Bloomberg. These three stocks are excluded from this analysis. All the stocks are split up in their sector, after which they are weighted in their sector. This means that the weight of the stocks in each sector aggregates to 100%. These adjusted weights are multiplied by the beta of the stocks, which results in the weighted sector beta. Figure 5.6 represents these sectors' physical and transition beta.

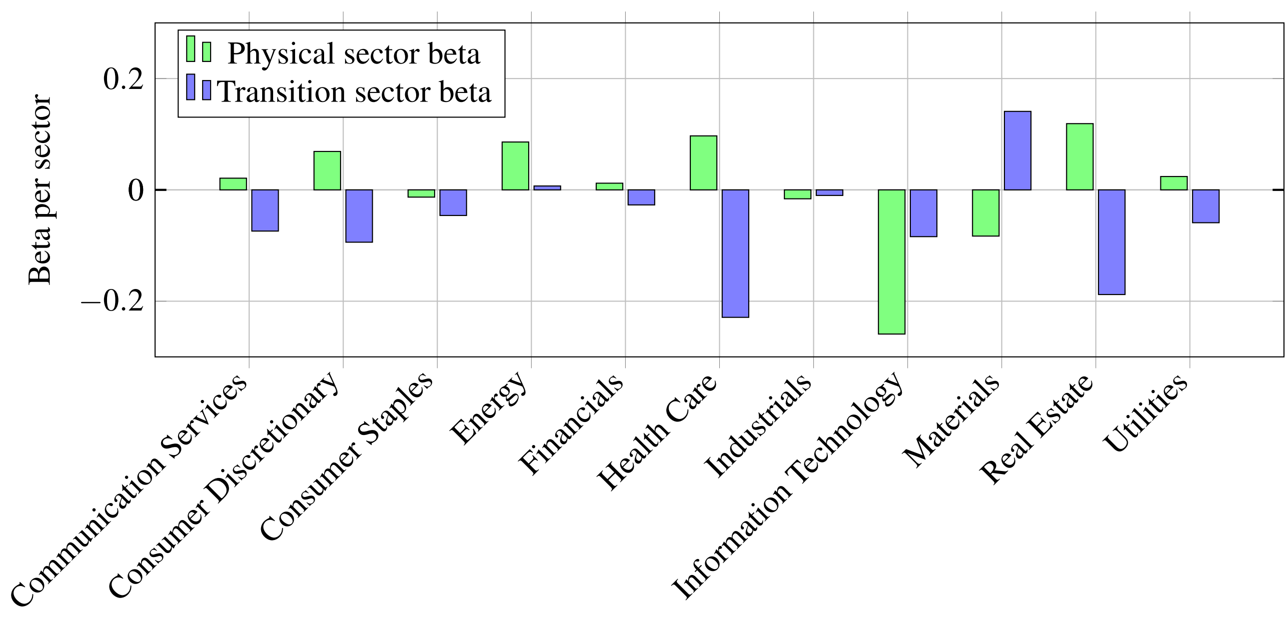


Figure 5.6: Physical and transition beta per sector

The Consumer Discretionary, Energy, Health care, and Real Estate sectors are the most sensitive to the physical risk factor, which means that if the PHY moves these sectors move the relative the most with the PHY. On the other hand, the Materials and Information Technology sector have opposite movement from the PHY risk factor. When looking at the composition of the risk factor,

Table 5.4, shows that each sector has high and low physical risk companies. Resulting in mixed results, not implying that the beta results come from this difference in high and low-physical risk companies. The Real Estate beta is largely influenced by two stocks (12.44% and 10.39%) that have a relatively high beta (0.282 and 0.274). In the same way, the weighted Information Technology beta is also largely influenced (11.43%) to a relatively low beta (-0.584).

On the other hand, the weighted transition beta shows a clear difference between the sectors. As discussed with the creation of the TRA portfolios in 5.8, the sectors Materials and Energy are mostly in the high-risk portfolios. This results in that most of these companies are exposed to high transition risk, which results in the outcome of relatively higher transition betas for these two sectors. On the other hand, the sectors that have mostly low transition risk, do not have relatively lower betas. Looking at the sectors' Financials, Information Technology, and Communication Services, they have a negative transition risk factor, but not relatively much lower than the other sectors. The Materials' beta is largely influenced by one stock (22.04%) that has a relatively high beta (0.098). The weighted Healthcare beta is also influenced by one stock (22.25%) to a relatively low beta (-0.769).

5.2.2 Benchmark comparison

The betas of the benchmark are represented in TTable 5.16, which shows a higher beta for TRA. The equity portfolio has a relatively lower beta for the transition risk factors compared to the ACWI. The beta for the physical factor is in both portfolios almost the same.

	ACWI	SMB	HML	UMD	**PHY**	**TRA**
Portfolio beta 2023	0.889	0.252	-0.112	-0.041	-0.0326	-0.072
Benchmark (ACWI) beta 2023	0.920	0.045	-0.0606	-0.0612	-0.0331	-0.033

Table 5.16: Benchmark beta comparison

Figure 4.2 shows the composition of the sectors in the ACWI, which is used to estimate the weighted sector beta for the ACWI. The same method is conducted as for the equity portfolio, so we weigh each stock in its sector. This results in a weighted beta for each sector for the ACWI, which is represented with the red bars in Figure 5.7. The equity portfolio has in some sectors a beta that is less exposed than the benchmark, such as the sectors of Communication Services, Materials, and Utilities. On the other hand, the sectors of Energy, Financials, and Industrials could be more exposed to the physical risk factor.

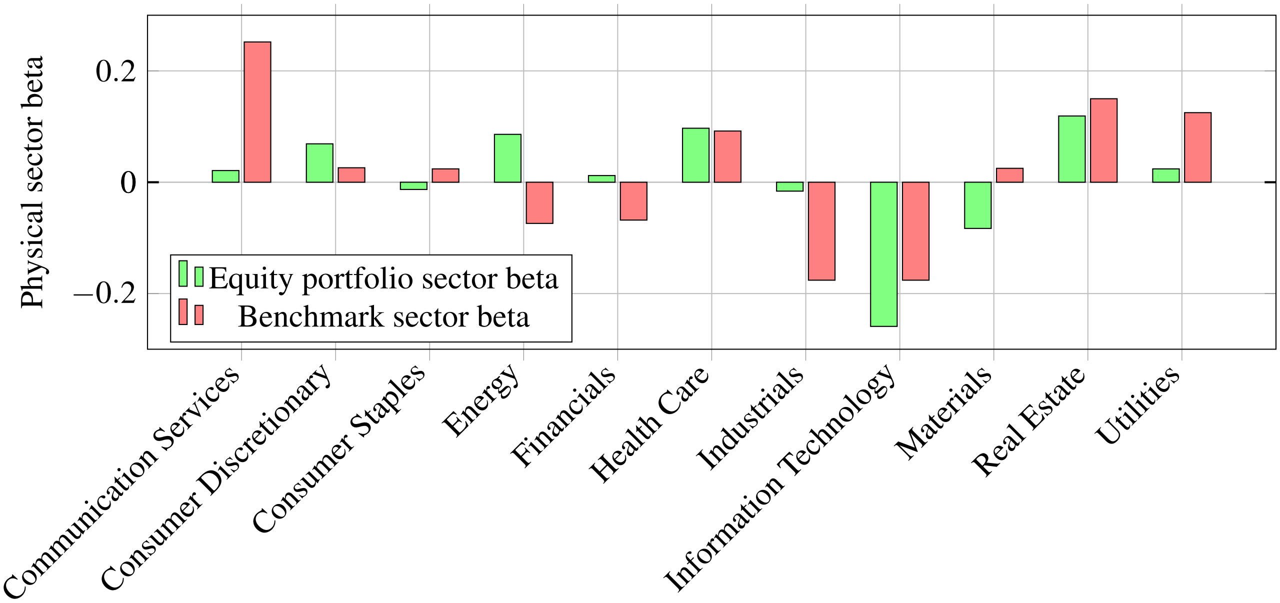


Figure 5.7: Physical sector beta with benchmark comparison

As we look at Figure 5.8, we see some sectors more exposed. The sectors of Energy, Industrials, and Materials have less exposure to the transition risk factor than the benchmark of ACWI does. However only the sector Consumer Discretionary has more exposure to the transition risk factor than the benchmark.

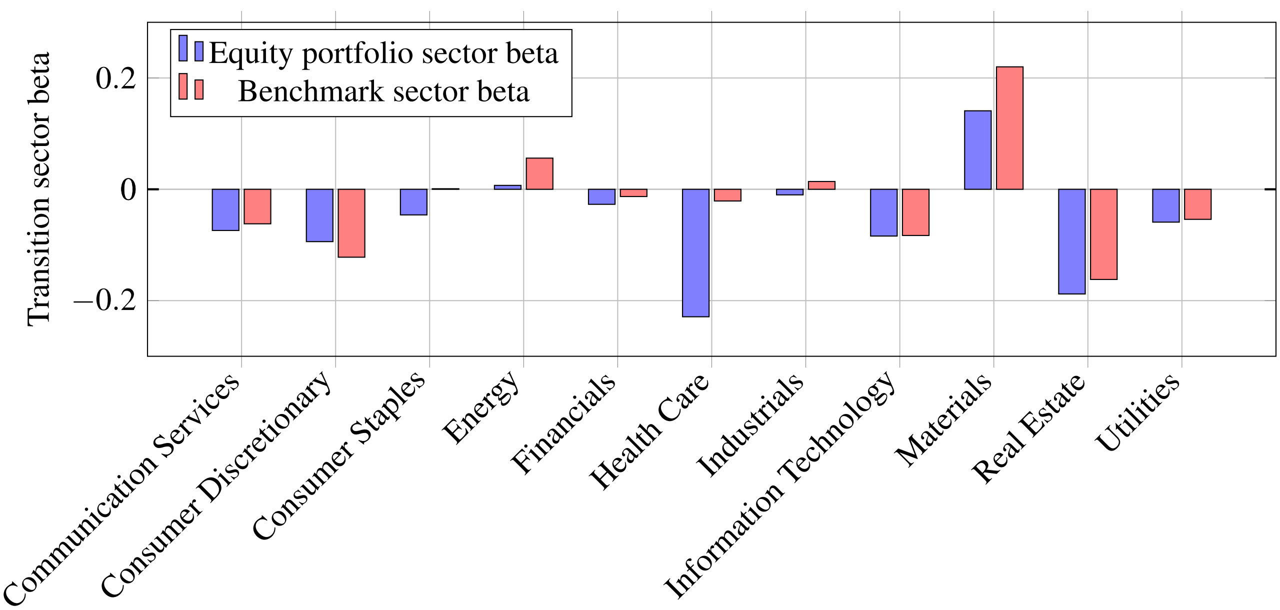


Figure 5.8: Transition sector beta with benchmark comparison

5.3 Market risk

The simulation of the potential losses of the equity portfolio is done under the assumption of normality of the residuals and risk factors. Appendix E.1 shows the residuals of eight random stocks in a Q-Q plot, under the assumption of normal distribution. The residuals of the eight stocks show quite a normal distribution, with some outliers. These eight Q-Q plots show that the assumption of normality does not lie far away from the data. However, these are eight out of the 1,486 stocks, there can be stocks that do not have a good fit with the normal distribution.

The risk factors are also assumed to have a normal distribution in the simulation of the potential losses. Appendix E.2 shows for each risk factor the Q-Q plot under the normality assumption and student t-distribution with different degrees of freedom. Most of the risk factors show more in line with the normal distribution than a student t-distribution with a low degree of freedom, thus a fatter tail. In the low degrees of freedom graphs, the samples often show an S-shaped form, which often indicates thinner or fatter tails than the student t-distribution. The only risk factor where a low degree of freedom could fit better is the HML risk factor. The HML shows in higher and lower degrees of freedom a good fit. Whereas, with higher degrees of freedom, the outliers lie further from the line. The Q-Q plots of each risk factor show that the normality assumption of the risk factors does not lie far away from the data that is used for the risk factors.

Figure 5.9 shows under these normality assumptions the potential weekly losses of the equity portfolio, based on the model used in this research with 10,000 simulations.

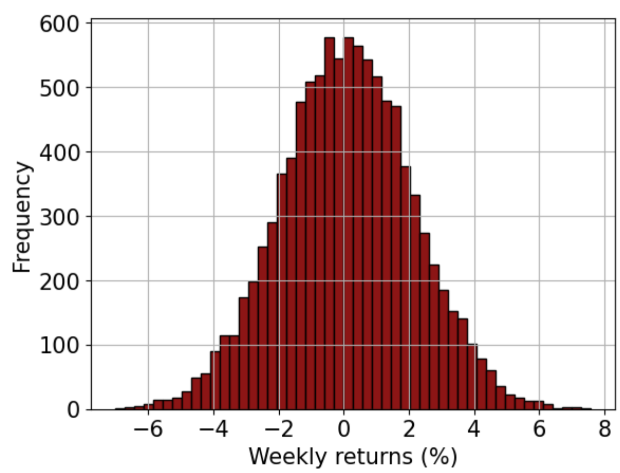


Figure 5.9: Simulated weekly portfolio returns

The 99%-VaR is extracted from the left tail, the 1% percentile, which represents the worst 1% weekly returns of the portfolio. As discussed, we can transform the weekly VaR and ES to annual with the equations 3.4 and 3.5. Table 5.17 presents the weekly and annual 99%-VaR and 99%-ES. Because we take the left tail, we take the 1% percentile, when looking at equation 2.1, $N^{-}1(0.01) = -2.33$, which means that we get a positive value of VaR and ES, because we multiply a negative value with a negative return.

	Weekly	Annual
99%-VaR	4.64 %	33.44 %
99%-ES	5.29 %	38.13 %

Table 5.17: VaR and ES of the simulation of potential losses of the equity portfolio

The VaR and ES are calculated with the biodiversity risk factor. It is important to validate the model used to calculate the VaR and thus the value of the VaR. One of the ways to validate the VaR is to back-test the current model, as discussed by Hull (2018). Back-testing is a crucial check for assessing the effectiveness of the risk measure. It evaluates how well the current method of calculating the measure would have performed in historical contexts. Back-testing involves examining how frequently losses over a day would have surpassed the calculated one-day 99% VaR under the current model. Instances where actual losses exceed the VaR are termed exceptions. Hull (2018) describes another method, aimed at estimating a confidence interval for VaR, namely the bootstrap method. The method generates changes in portfolio value based on historical movements in the market. Then, it repeatedly samples from these changed portfolios to create many new datasets. The VaR is calculated for each of these new datasets. The 95% confidence interval for VaR is determined by the range between the 2.5th and 97.5th percentile of the distribution of VaRs calculated from these datasets. Resulting in the range where the VaR lies with a certain confidence. It is important to validate the model and to look at the calculated value of VaR. However, it lies out of the scope of the thesis to investigate the model. For further research, it is important to look at the model validations to see how the model performs.

Sensitivity test

As discussed in the method, the biodiversity risk factors will be transformed into a student t-distribution with different degrees of freedom. The increased fat tail of the biodiversity risk factors could cause the portfolio returns to also have fatter tails. The 99%-VaR shows a lot of fluctuations. Therefore, we looked at the 99%-ES, which should represent a more average value. Figure 5.10 shows the 99%-ES with different degrees of freedom. Here we see a clear decrease in the expected shortfall when there is a higher degree of freedom. When the degrees of freedom get higher it becomes more flat resulting from converting to the normal distribution.

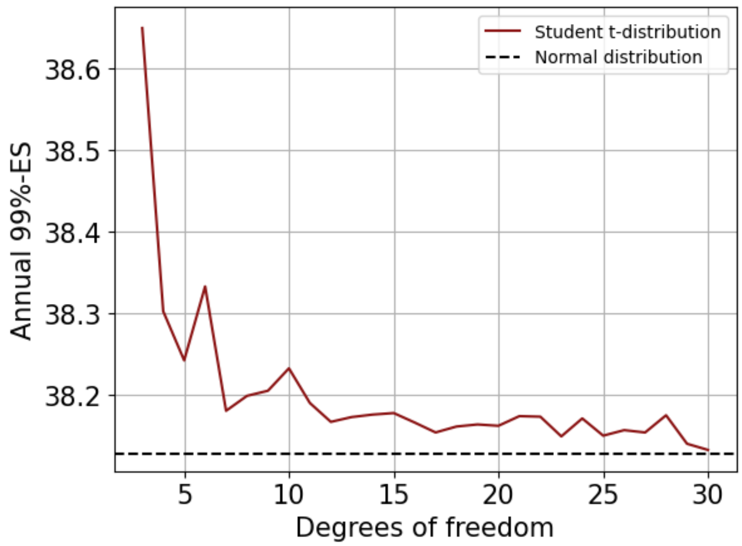


Figure 5.10: Annual 99%-ES across different degrees of freedom

It is clear that the student t-distribution with a lower degree of freedom results in a higher annual 99%-ES. However, as can be seen in Figure 5.10 the differences between the low degrees of freedom and the normal distribution are small. This could mean that the biodiversity risk factors do not have a lot of effect on the potential losses of the equity portfolio. As a result, the equity portfolio currently shows robustness against extreme values of the biodiversity risk factors.

Simulation without biodiversity risk factors

Another analysis that we described in the method was that of comparing the simulation of the model with biodiversity risk factors and one without these factors. Table 5.18 shows the results of both simulations without the residuals, which show a minimal higher 99%-Var for the simulation with both biodiversity risk factors. The difference between both simulations is small but existing, showing that there could be an impact of the biodiversity risk factors on the 99%-VaR. However, the difference between both simulations is small, showing more evidence that the biodiversity risk factors do not have that much influence on the VaR. Currently, potential losses of the equity portfolio are not significantly impacted by the biodiversity risk factors, indicating robustness against these factors.

	$R_{\text{biodiversity}}$	R_{normal}
99%-Var	33.86%	33.74%
99%-Es	39.14%	38.82%

Table 5.18: VaR and ES of the simulation with and without biodiversity risk factors

5.4 Conclusion

This chapter discussed the results of using the framework described in Chapter 3. The results give answers to the following research questions.

How is an equity portfolio exposed to physical and transition risks associated with biodiversity?

The exposure to the physical and transition biodiversity risk in the equity portfolio is assessed by estimating the betas for both the physical and transition risk factors. The betas are estimated with a biodiversity time series regression, which shows the sensitivity of each stock regarding each risk factor. The objective of these betas is the sensitivity to each factor, meaning that negative betas mean low sensitivity regarding the factors. The exposure of the portfolio regarding the biodiversity risk factors is described in Table 5.12, which shows negative values for both biodiversity risk factors. This indicates with the objective that we set, that the equity portfolio shows a low exposure to the biodiversity risk factors. Compared to the ACWI, the equity portfolio shows almost the same sensitivity to the physical factor but less exposure to the transition factor. The low negative betas show that there is low exposure to the biodiversity risk factors, but it also does mean that both factors do not influence the returns of the stocks in the portfolio much.

In the end, the betas of the sector were also compared to see how the equity portfolio performed in comparison to the ACWI. This shows some sectors have stocks that are more sensitive to biodiversity risks than the ACWI. This could be because the equity portfolio invested a larger part of its portfolio in more exposed companies or invested less in companies that are less exposed to biodiversity than the ACWI.

What is the impact of the biodiversity risks on the market risk of an equity portfolio, and what are the implications of these risks?

The other part that is discussed is the impact of the biodiversity factors on the market and the potential losses of an equity portfolio. Section 5.1 describes that when there is a positive risk premium, companies require a higher risk premium when they are more exposed to the risk factor. As discussed, the physical risk does at the moment not have a positive risk premium, which means that companies that are more exposed do not require a higher risk premium. On the other hand, the transition risk has a positive risk premium, which shows that these risks are priced in. These risk premiums show how investors look at both biodiversity risks at the moment.

The potential returns of the equity portfolio are simulated under the assumption of normality, resulting in a distribution of the returns. The 99%-VaR and 99%-ES are then calculated from the left percentile of the distribution, which results in a value for both risk metrics, described in Table 5.17. This shows the market risk of the equity portfolio which includes both biodiversity risk factors. The impact of the biodiversity risk factors is discussed by two sensitivity analyses, which try to capture the impact. The first one is to fatten the tail of both biodiversity risk factors, which would result in more extreme values. This is done by transforming the distribution to a student t-distribution with a low degree of freedom. This transformation shows in Figure 5.10, that the fatter the tails, the higher the 99%-ES. However, the differences between the various degrees of freedom are small. Showing that there is an impact of the biodiversity risk factors, but a small one. The other analysis is a comparison between a model with and without the biodiversity factors. This analysis also shows an impact of the biodiversity risk factors but also a small impact. These results show a small impact of the biodiversity factors on the potential losses of the equity portfolio and show that the portfolio is robust against these risks at the moment.

Chapter 6

Conclusion and Discussion

This chapter reflects on the research goal set in this research. It discusses the limitations of the framework, such as the data and model used. This discussion leads to considerations for future improvements and developments based on this framework. Finally, the policy implications of the research will be discussed.

6.1 Conclusion

In the introduction, we established the research goal to address the core problem: the lack of understanding regarding the exposure to risks associated with biodiversity loss and their impact on the market risk of an equity portfolio. This research developed a framework to address this goal:

How can a framework be established to identify biodiversity risks and assess market risks in equity portfolios related to biodiversity loss?

The framework established is an adaptation of the Fama-French model, which integrates additional factors into the CAPM model. The Fama-French model allows for the incorporation of the biodiversity risk factors into the CAPM return equation for a specific stock. These biodiversity risk factors are determined using a long-short portfolio, where we take long positions in high-risk companies and short positions in low-risk companies. These portfolios provide weekly returns over three years for the biodiversity risk factors, specifically the physical and transition risk factors. The average weekly returns of these risk factors indicate either a positive or negative risk premium, showing whether investors demand a risk premium for holding high-risk stocks. This research reveals that the physical risk has a negative risk premium, while the transition risk has a positive risk premium. Consequently, the transition risk is priced in according to the MSCI data.

The second step in the framework involves calculating the sensitivity of stocks in the equity portfolio to both biodiversity factors. The OLS time series regression is utilized to estimate the sensitivity of each stock to each risk factor in the equation. Equation 3.3 is used in this research, including six different risk factors. The time series regression gives a beta, representing the sensitivity, for each of the risk factors. These betas are then used to estimate the portfolio betas, indicating the overall sensitivity of the portfolio to the risk factors. For the equity portfolio, this step resulted in negative exposure to both biodiversity risk factors. This step in the framework reveals the exposure of stocks in the portfolio to biodiversity risks.

The final step in the framework involves calculating the market risk associated with biodiversity loss. With the residuals, risk factors, and betas at our disposal, potential portfolio losses can be estimated, leading to the calculation of the 99%-VaR and 99%-ES. Initially, a simulation is done assuming the normality of the risk factors and residuals, although, in practice, this assumption often proves inaccurate due to fatter tails. This simulation provides values for the 99%-VaR and 99%-ES for the equity portfolio. Subsequently, the influence of biodiversity risk factors on the risk metrics is analyzed through two approaches. Firstly, the distribution of biodiversity risk factors is transformed into that of a student t-distribution, characterized by fat tails at low degrees of freedom. This analysis reveals a higher ES, as expected, but with minor deviations from a normal distribution. Secondly, a comparison is made with a model without the biodiversity risk factors. This comparison indicates a lower 99%-VaR and 99%-ES for the model without biodiversity risk factors, but with small differences. In this research, it appears that biodiversity risk has some impact on potential losses in the equity portfolio, but minimal.

In conclusion, this research establishes a framework for identifying biodiversity risk in an equity portfolio. Furthermore, a framework is developed for assessing the market risk of an equity portfolio incorporating these biodiversity risk factors. This concludes in a framework consisting of three steps, which enables the estimation of exposure to biodiversity risks and investigates the influence of biodiversity risk on the market risk of an equity portfolio.

6.2 Discussion

In this section, we discuss the limitations of both the framework and the research, while also proposing potential improvements for both.

Biodiversity data

In this study, we relied on MSCI data to capture both biodiversity risk factors. As discussed, this dataset enables us to differentiate between high and low-risk companies. In Chapter 4.4, we highlighted that biodiversity data from different providers lacks correlation. Consequently, using a different provider may lead to the creation of portfolios with different compositions, resulting in alternative risk factors from those used in this research. Investigating various providers could analyze the robustness of biodiversity risk factors to different data sources.

Another aspect to consider regarding biodiversity data is that it is a very new topic. Consequently, fully capturing the totality of the risk remains challenging. As discussed, physical risk is often defined as ”the dependence on ecosystems”. While our research uses a dataset focusing on geographical dependence, it does not consist of all the aspects of physical risk. Our findings indicate that physical risk is currently not priced in using the MSCI dataset. One possible explanation is that the dataset fails to adequately capture the physical risk of companies. Future availability of datasets could provide a more complete perspective.

The MSCI datasets we used sometimes lack clarity regarding their methodology and the data they incorporate. As a result, we cannot provide a clear understanding of how the data used in this research is constructed. This is partly due to confidentiality concerns and partly because certain information is missing. For example, we are unsure about the frequency of dataset creation or updates. It is possible that these datasets were created in 2020 and refreshed annually, or they might undergo monthly updates. Currently, this information is unavailable to us. However, it is possible that in the future, more information about each dataset will become available, providing a better understanding of the datasets used in this research.

Model assumptions and validations

The framework developed in this research involves certain choices and assumptions, which require some discussion. Firstly, there is the decision on how to construct portfolios, accomplished by sorting based on the 20% percentile of large and small companies and incorporating biodiversity data. These decisions influence the composition of high and low-risk portfolios and consequently, the biodiversity risk factors. Changing the sorting method could impact these portfolios and potentially alter the biodiversity risk factors, leading to different results. It would be insightful to explore how various sorting approaches affect the results of this study.

The Fama-French factors used in this research are based on developed markets. As discussed, the equity portfolio and the ACWI also consist of emerging markets. The market factor is replaced by the ACWI. However, the other three factors are still based solely on developed markets. This could lead to difficulties in predicting the returns of stocks in emerging markets. As there were no factors including both developed and emerging markets, it was chosen to still use the developed markets. When Fama-French is updated with factors for both developed and emerging markets, these should be used in the research.

Thirdly, the biodiversity time series regression conducted in this research aims to determine the exposure to biodiversity risk factors. Chapter 5.2 discusses the statistical outcomes, indicating that the model currently explains only a modest percentage of equity portfolio returns. Further validation of the test data and time series regression is essential to evaluate the model's explanatory power. Out-of-sample data validation is one method for assessing the regression model's validity, which is crucial for future research to ensure the model's efficiency.

Additionally, the framework includes simulating potential losses of the equity portfolio, assuming normality, which may not hold true in practice. As a sensitivity test, biodiversity risk factors are transformed into a student t-distribution, while other risk factors still have the normal distribution assumption. Investigating alternative distributions for risk factors is interesting for further sensitivity tests. These simulations result in VaR calculations, serving as a risk metric for the market risk of the equity portfolio. As discussed in Chapter 5.3, it is important to validate VaR further in these simulations, with one approach being the bootstrap method.

Equity portfolio

This research centers on the equity portfolio, focusing on the stocks' sensitivity to biodiversity risk factors. The investments in the equity portfolio are based on ESG criteria, incorporating environmental, social, and governance scores in the composition. Additionally, the equity portfolio leans towards risk aversion, implying a limited inclusion of high-risk stocks. In this study, we observe that the equity portfolio shows low sensitivity to both biodiversity risks. One possible explanation for this low sensitivity could be the implementation of ESG criteria, which may have already excluded many high-risk companies from the portfolio. Consequently, the equity portfolio appears resilient to biodiversity risks due to these investment choices. It would be interesting to investigate whether investment portfolios that deviate from such criteria and have a different risk appetite display higher sensitivity to biodiversity risk factors.

Correlation with climate risk factor

As mentioned in the introduction, biodiversity loss is closely linked with climate change, with some similarities and differences. Climate change primarily focuses on CO_2 emissions, while metrics for estimating biodiversity loss remain less clear. The biodiversity datasets used by MSCI may be influenced by climate change metrics, such as CO_2 emissions, which also impact biodiversity loss. Currently, we lack a weekly return representing climate change risk, hindering comparisons with biodiversity risk returns. One potential approach could involve creating a climate risk factor using similar methods to those used in this study. If there is the availability of climate change risk returns, it would be valuable to explore the correlation with the biodiversity risk factors.

Future use

This research establishes a framework for estimating sensitivity to physical and transition biodiversity risk factors, assisting investors in investigating their exposure to biodiversity risks and informing investment decisions regarding biodiversity loss. Companies in the Energy, Materials, and Industrials sectors typically have high exposure to transition risk. Consequently, investors seeking to mitigate transition risk should consider divesting from these sectors. However, this may lead to a concentrated portfolio, which may not always be advantageous. Therefore, investors should carefully weigh the implications of making investment choices based on biodiversity risk exposure.

6.3 Future research

This research represents the first attempt to develop a framework for integrating biodiversity risk exposure into a market risk model. However, there are recommendations listed below to improve or extend the framework.

Improve the model

The model employed in the framework relies on certain assumptions and lacks certain validations. It is suggested to conduct further analysis to refine the model created in this research. Recommended validation includes that of the biodiversity time series regression and the VaR. Furthermore, additional analysis could explore the impact of changes in biodiversity portfolios, distributions, and the equity portfolios used.

Biodiversity data analysis

As discussed, there are some discussion points regarding the biodiversity data from MSCI. For future research, it would be interesting to investigate how the biodiversity risk factors change when using other datasets. Additionally, as datasets evolve to include a broader understanding of biodiversity risks, it is important to examine these datasets. These new datasets could provide a clearer picture of the risk exposure.

Other risk models

While this research primarily focuses on the impact of biodiversity risk on the market risk of equity investment portfolios, it would be worthwhile to explore other risk models. Financial institutions and central banks are not only exposed to biodiversity risk through their investments but also through their lending. Therefore, it is important to further research the impact of biodiversity risk on credit risk or interest risk and integrate these aspects into risk models.

Portfolio based on biodiversity metrics

The estimation of betas offers the opportunity to calculate the portfolio's exposure to both biodiversity risks. In this research, we computed the portfolio beta based on the weight of a stock and its sensitivity to the risk factors. This resulted in the portfolio beta, which can be used to estimate the optimal composition of the portfolio with respect to exposure. For future research, it would be interesting to explore how an equity portfolio should be composed to achieve optimal exposure. Additionally, it would be valuable to assess the performance of this optimal portfolio compared to the current portfolio.

6.4 Policy implications

As discussed, the framework contributes to the literature, besides that the framework also could have policy implications for De Nederlandsche Bank, other central banks, banks, pension funds, and insurers.

De Nederlandsche Bank and other central banks

This research, conducted in collaboration with De Nederlandsche Bank, provides a model that can be used by their risk management team. The model contributes to their market risk assessment by incorporating a biodiversity risk factor. This enables them to evaluate their exposure to biodiversity in their portfolio and make informed investment decisions. Other central banks can also use the framework in their market risk assessment to incorporate biodiversity risks.

Financial institutions

Financial institutions rely on risk metrics such as credit risk, market risk, and interest risk to ensure financial stability. However, the emerging topics of climate change and biodiversity loss are gaining importance and need to be incorporated into these risk models. Currently, biodiversity risks are not integrated into the risk models of banks, pension funds, and insurers. The framework developed in this research offers a method to include biodiversity risk in market risk models.

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Appendix A

Biodiversity scenario's

In this section various scenarios will be reviewed. One of the possibilities to assess market risk is scenario analysis regarding biodiversity loss, due to this an overview is created of the scenarios that is represented in the literature. Separating scenarios for physical and transition risks. Following the paper by Maurin et al. (2022) and further literature research, these scenarios regarding biodiversity are listed. Scenarios provide qualitative and/or quantitative representations of potential futures, which can be used to assess the market risk in a future scenario where biodiversity loss is incorporated. In the context of biodiversity, these characterize the development of components within an ecosystem. The scenarios could help to describe possible futures in situations characterized by high uncertainty. (Maurin et al., 2022)

Physical risk

Exploratory scenarios are designed to evaluate physical risks and shocks associated with biodiversity loss, as stated by Maurin et al. (2022). These scenarios investigate possible futures, based on potential paths of biodiversity drivers. As a results, it is possible to assess economic responses to shocks coming from specific changes or losses of biodiversity. Consequently, the exposure to these scenarios can be calculated with the help of the dependence score. These scenarios reflect a physical biodiversity shock, with the consequence that companies that are dependent of are in sensitive areas have a higher risk of negative consequences of these shocks.

Within the literature review methodology done by Maurin et al. (2022) the paper that is appropriate for analyzing physical shocks is the scenario by Johnson et al. (2021). This paper reports a scenario wherein biodiversity tipping points are exceeded and reports economic responses from these tipping points. Johnson et al. (2021) created this scenario for biodiversity loss with a model to assess the interaction between ecosystems and the economy to 2023.

Johnson et al. (2021) introduces an innovative modeling framework that integrates specific ecosystem services into a computable general equilibrium (CGE) model. CGE models belong to a category of economic models to assess the potential impact of policy shifts, technological advancements, or other external influences on an economy. This integration enables the examination of the impacts between changes in ecosystem services and the global economy from 2021 to 2030. The model uses four ecosystem services: crop pollination, climate regulation through carbon storage, food provision from marine fisheries, and timber supply. The paper evaluates the connections between the decline of these chosen ecosystems and the performance of sectors dependent on these services. It also investigates the broader economic impact through trade and shifts in production demand. A comparison is drawn between the baseline scenario and two scenarios, ”business-as-usual” (BAU) and ”partial ecosystem collapse” scenario, simulating interactions between the ecosystems and the global economy up to 2030.

- *Baseline scenario*
  This scenario estimates the potential state of the world economy in 2030, including variables like population growth and technological advancements. However, this baseline scenario has a limitation, it does not take into account the impact of changes in the economy on the demand of ecosystem services. According to this scenario, the world in 2030 experiences moderate economic and population growth.

- *Business-as-usual scenario*
  The second scenario addresses the limitation of the baseline scenario by considering changes in ecosystem services. This known as the BAU scenario, it provides a more realistic representation of the economy in 2030 and serves as the basis.

- *Partial ecosystem collapse scenario*
  The third scenario entails a partial collapse of various ecosystem services. The tipping point that is used in this analysis is a collapse of wild pollination, marine fisheries and timber provision from tropical forests, with a reduction in the ecosystem of 90%.

The scenarios in the report by Johnson et al. (2021) offer insights into the potential paths and ranges of outcomes associated with different scenarios. While this tool is currently the best available for assessing biodiversity and ecosystem service, it has limitations in terms of the range of ecosystem services considered and the relatively short time horizon analyzed. Given the limited application to a specific set of ecosystem services, the scenarios presented here may indicate lower impacts in the real world. As more types of ecosystem services are studies in the future, it is likely to expect larger estimates of economic impacts.

The effect on the GDP is calculated in the scenario of a partial collapse. Resulting in a -2.3% change in real GDP in this scenario, compared to the BAU scenario and a decline by 10% of the global GDP growth of 2021-2023. Moreover, mostly low-income countries, such as south Asia and sub-Saharan Africa are projected to have declined real GDP of 6-10% in the partial ecosystem collapse scenario. This is due to the high dependencies of these regions on natural ecosystems.

Transition risks

On the other hand, to assess the transition risks and shocks, there are two categories: target-seeking scenarios and policy-screening scenarios. Target-seeking scenarios pinpoint specific objectives, often in terms of achievable targets, and then explore various paths to reach those goals. For example, there could be scenarios focused on reversing the biodiversity trend by 2050. Policy-screening scenarios enable assessments to predict the impact of different regulations on environmental outcomes. These scenarios involve testing policies on both the supply side and the demand side within a specific industry, reflecting the economic outcome of regulations. Consequently, both types of transition scenarios can simulate the impact of a transition by means of targets or policies on biodiversity and the overall economy. (Maurin et al., 2022)

This research focuses on the economic outcomes of biodiversity scenarios. Therefore the focus of is on the papers with an economic outcome of a transition scenario. This is again the paper of Johnson et al. (2021), but also the papers by Cheung et al. (2019) and Costello et al. (2016). The latter papers only discuss the consequences of scenarios on the ecosystem of fisheries. Discussing the anticipated cost of certain scenarios and the additional benefit of other scenarios. As the focus of this research is not solely on fisheries, these papers will not be further discussed.

The paper by Johnson et al. (2021) discusses various scenarios and its economic outcomes. On the one hand there are scenarios of proposed policies and on the other hand there is a scenario that comes from an already defined global goal. The paper explores the "30x30" goal, a global initiative to protect 30% of Earth's land and sea by 2030 to preserve biodiversity. To calculate the opportunity cost, the study identifies key areas for conservation under the 30x30 goal. It then compares the 2030 GDP to a BAU scenario, considering in the economic impact of removing land from production. The 30x30 goal shows a positive global impact on biodiversity, with a 29% improvement over the BAU scenario. This not only reverses biodiversity loss but also achieves a 50% improvement beyond BAU levels. However, the economic impact of the 30x30 scenario is initially negative, with a \$115.4 billion decrease in GDP, equating to a 0.1% drop. When adjusted for climate mitigation benefits, the GDP decrease is smaller, at \$13.4 billion, or 0.01%. Despite the initial economic loss from land use restrictions, the gains from enhanced ecosystem services and reduced carbon emissions nearly balance it out, suggesting the economic feasibility of the 30x30 goal from a global perspective.

Conclusion

The only outstanding study is by Johnson et al. (2021), focusing primarily on global GDP and regional GDP changes under physical and transition scenarios. This information, however, is insufficient for understanding the impact of these scenarios on equity markets, making it inadequate for assessing market risks associated with biodiversity loss. Currently, there are no fitting scenarios to evaluate the market risks coming from biodiversity loss.

Appendix B

Data

B.1 Fama-French developed market factors

Country	Developed	Developed ex US	Europe	Japan	Asia Pacific ex Japan	North America
Australia	✔	✔			✔	
Austria	✔	✔	✔			
Belgium	✔	✔	✔			
Canada	✔	✔				✔
Switzerland	✔	✔	✔			
Germany	✔	✔	✔			
Denmark	✔	✔	✔			
Spain	✔	✔	✔			
Finland	✔	✔	✔			
France	✔	✔	✔			
Great Britain	✔	✔	✔			
Greece	✔	✔	✔			
Hong Kong	✔	✔			✔	
Ireland	✔	✔	✔			
Italy	✔	✔	✔			
Japan	✔	✔		✔		
Netherlands	✔	✔	✔			
Norway	✔	✔	✔			
New Zealand	✔	✔			✔	
Portugal	✔	✔	✔			
Sweden	✔	✔	✔			
Singapore	✔	✔			✔	
United States	✔					✔

Figure B.1: Overview of countries in the developed 3 factors

B.2 ENCORE data

The ENCORE database provides a dependence score for a production process, which can be of interest for assessing physical risk. The indicator for physical risk in this context could be defined as 'dependence on ecosystem services.' The ENCORE database gives a dependence score to each production process. The range of scores is Very Low (VL), Low (L), Medium (M), High (H), Very High (VH). For each production process, ENCORE identifies its dependence on specific ecosystem services selected from the list. It should be noted that for a production process not all 21 ecosystem services have associated scores, only those relevant to a particular production process receive a dependence score. These scores are derived from a literature review and expert interviews conducted by ENCORE. The database is organized into 11 unique sectors, such as energy, information technology, and materials. Each sector contains unique sub-industries following the Global Industry Classification Standard (GICS). While ENCORE mentions 157 different sub-industries, we found 152 unique sub-industries in our examination of the database. Each sub-industry consists of one or more production processes, with some sub-industries containing multiple production processes. Furthermore, different sub-industries can consist of the same production process, resulting in them sharing the same dependence score.

Figure B.2 provides an overview of four sub-industries. The Consumer Staples sector includes sub-industries like Agricultural Products and Food Retail, with Agricultural Products consisting of nine different production processes, including Aquaculture and Saltwater wild-caught fish. Each of these production processes has a dependence score based on the ecosystem services they rely on. Notably, these production processes demonstrate varying numbers of dependence on ecosystem services, with Aquaculture depending on 13 ecosystems, while Infrastructure holdings rely on just 2. Additionally, the sub-industry Health Care Technology and Food Retail both include the same production process, namely Infrastructure holdings.

For assessing transition risk, one of the indicators could be the impact on ecosystems, and ENCORE provides interesting data in this regard. The impact score in ENCORE is derived from the same production processes, sub-industries, and sectors as the dependence score. However, unlike the dependence score, the impact score is based on 12 impact drivers. Each production process is assessed for each of these 12 impact drivers, considering factors such as frequency, time frame, and severity. This assessment results in an impact score, ranging from Very Low (VL) to Very High (VH). Some impact drivers may not receive a score by ENCORE, indicated as ND due to insufficient information. Figure B.3 provides an overview of the impact database in ENCORE. The structure shows the sector, sub-industry, and production processes, similar to the dependence

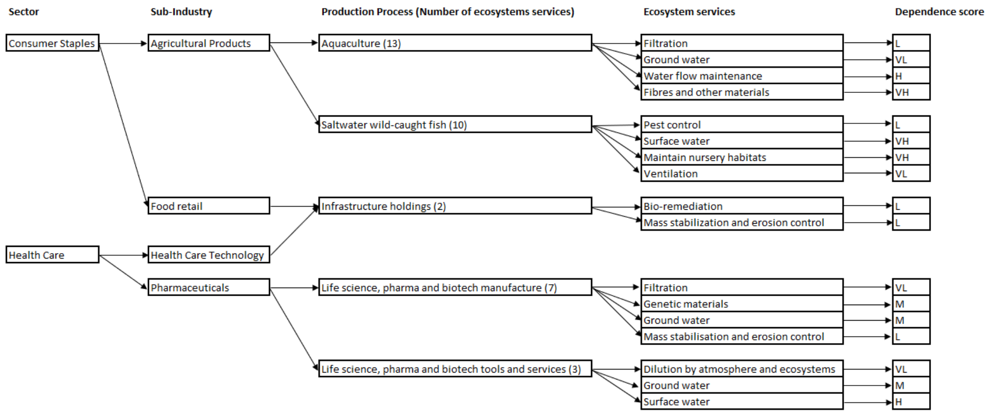


Figure B.2: Overview of ENCORE dependence score database

score. However, for each production process, the 12 impact drivers are assessed, with some scores marked as ND. Additionally, different sub-industries may still share the same production processes, leading to identical impact scores.

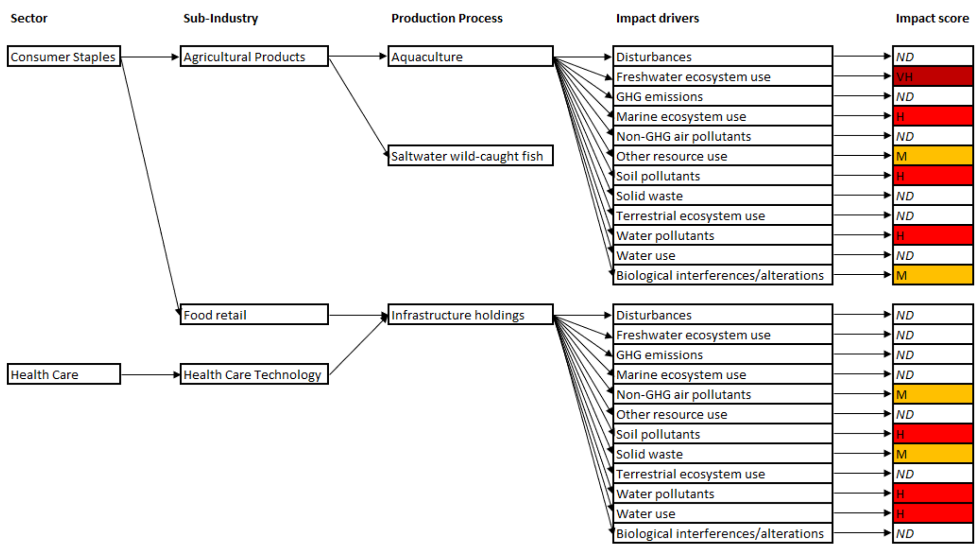


Figure B.3: Overview of ENCORE impact drivers database

Appendix C

Biodiversity portfolios composition

Country	High-risk portfolio (%)	Low-risk portfolio (%)
Australia	–	3.13
Belgium	–	3.13
Brazil	–	1.56
Canada	–	1.56
Chile	–	1.56
China	47.68	–
Denmark	–	4.69
Finland	–	1.56
France	–	4.69
Germany	–	1.56
Greece	–	1.56
Hungary	–	1.56
India	7.95	–
Indonesia	3.31	–
Italy	–	6.25
Japan	–	4.69
Kuwait	–	1.56
Luxembourg	–	3.13
Malaysia	1.32	–
Mexico	2.65	–
New Zealand	0.66	–
Norway	–	1.56
Philippines	0.66	–

Country	**High-risk portfolio (%)**	**Low-risk portfolio (%)**
Poland	–	1.56
Saudi Arabia	–	7.81
Singapore	–	9.38
South Africa	–	6.25
South Korea	–	3.13
Spain	–	1.56
Switzerland	–	7.81
Netherlands	–	7.81
Turkey	–	1.56
UAE	–	4.69
UK	–	3.13
US	35.76	4.69

Table C.1: Country composition of the physical portfolios

Country	**High-risk portfolio (%)**	**Low-risk portfolio (%)**
Australia	3.33	1.02
Brazil	4.17	1.02
Canada	5.00	2.04
Chile	1.67	–
China	22.5	–
Colombia	0.83	–
France	0.83	4.08
Germany	–	3.06
Greece	0.83	1.02
Hong Kong	–	1.02
India	5.00	1.02
Indonesia	5.83	–
Italy	0.83	2.04
Japan	0.83	7.41
Malaysia	0.83	–
Mexico	1.67	–
New Zealand	0.83	–
Norway	0.83	–
Poland	–	1.02

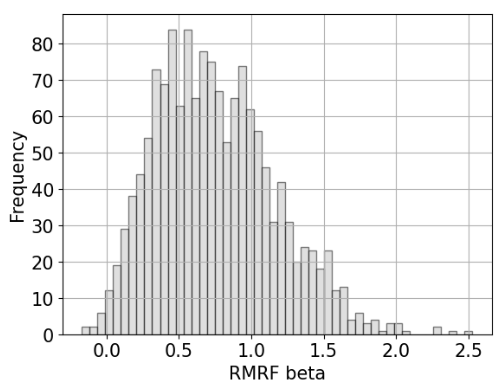
Country	**High-risk portfolio (%)**	**Low-risk portfolio (%)**
Saudi Arabia	–	3.06
Singapore	–	3.06
South Africa	5.00	2.04
South Korea	2.50	9.18
Spain	0.83	1.02
Switzerland	–	2.04
Taiwan	1.67	1.02
Thailand	0.83	–
Netherlands	–	1.02
Turkey	1.67	1.02
UAE	–	1.02
UK	5.00	5.10
US	25.00	45.92

Table C.2: Country composition of the transition portfolios

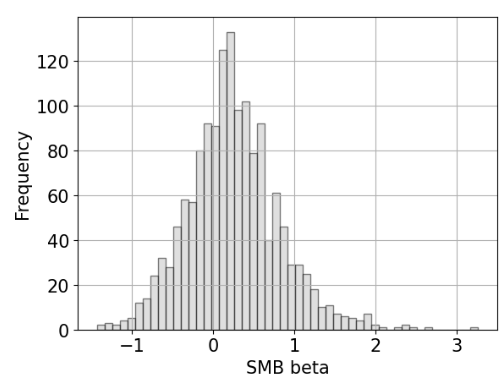
Appendix D

Results of the regression

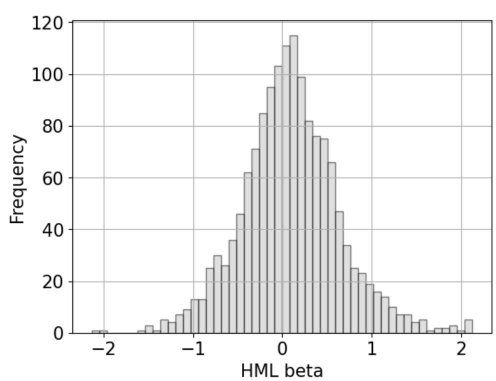
D.1 Results of the regression with Fama-French factor



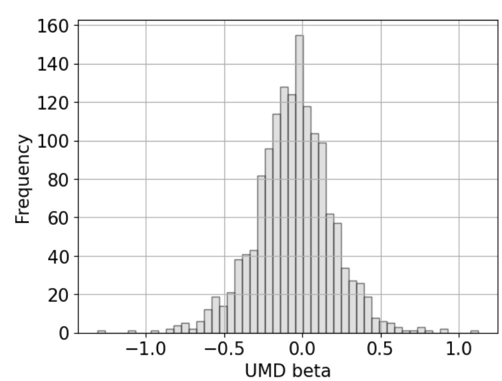
(a) Frequency of the RMRF beta



(b) Frequency of the SMB beta



(c) Frequency of the HML beta



(d) Frequency of the UMD beta

Figure D.1: Frequency of the Fama-French risk factor betas

D.2 Results of the regression with the ACWI as market factor

	PHY	TRA	RMRF	SMB	HML	UMD
PHY	1.000					
TRA	0.056	1.000				
RMRF	0.111	-0.557	1.000			
SMB	0.001	0.007	0.009	1.000		
HML	-0.239	0.529	-0.362	-0.118	1.000	
UMD	0.028	0.280	-0.210	-0.026	0.205	1.000

Table D.1: Correlations between the risk factors with the AWCI

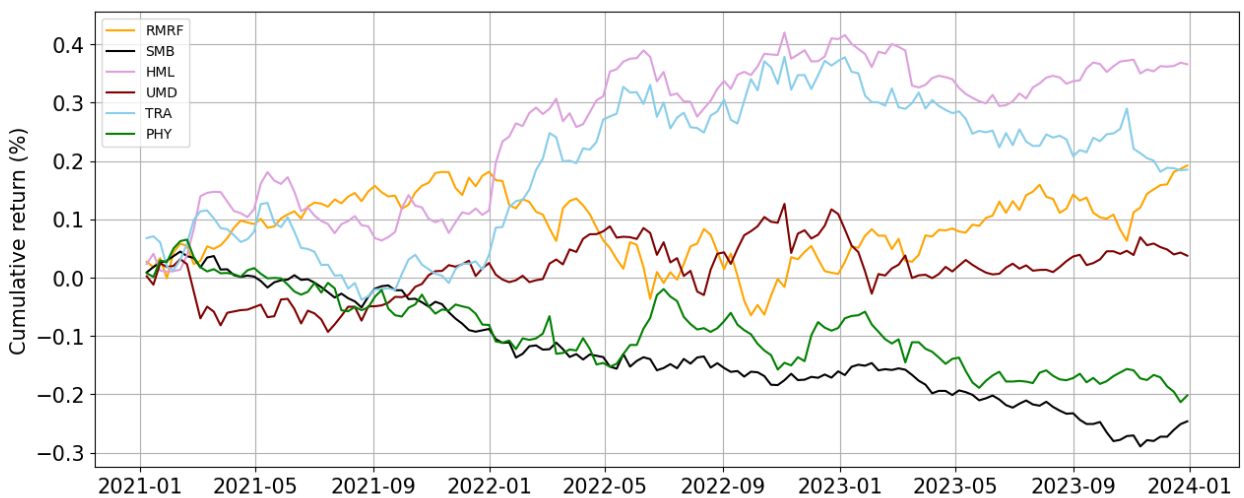
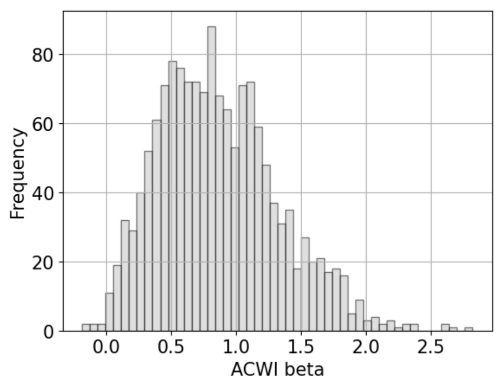
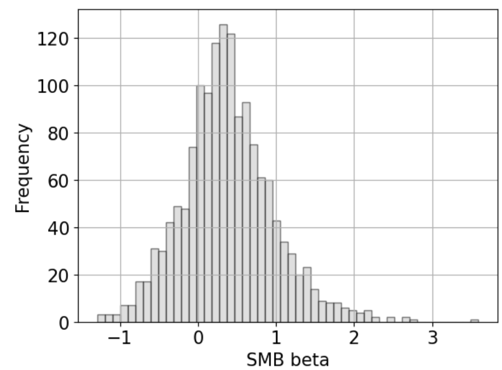


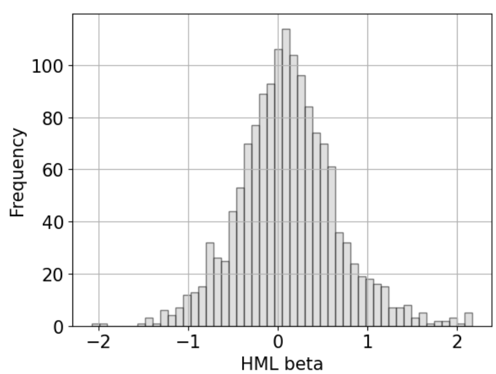
Figure D.2: Performance of the risk factors with the ACWI



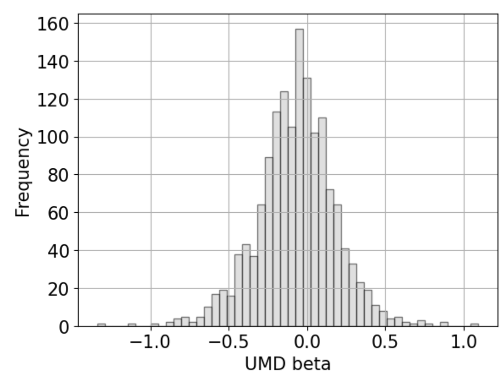
(a) Frequency of the ACWI beta



(b) Frequency of the SMB beta with the ACWI



(c) Frequency of the HML beta with the ACWI



(d) Frequency of the UMD beta with the ACWI

Figure D.3: Frequency of the risk factor beta with the ACWI

Appendix E

Assessment of distribution assumptions

E.1 Residuals fit: Q-Q plots

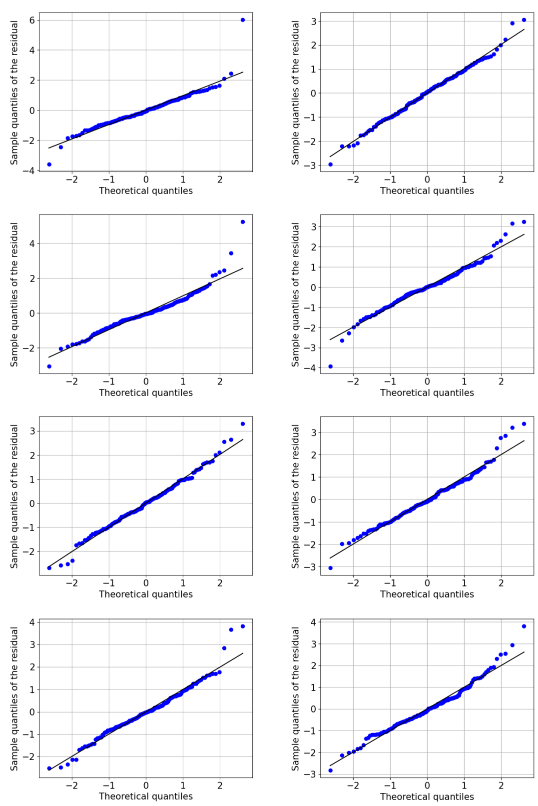
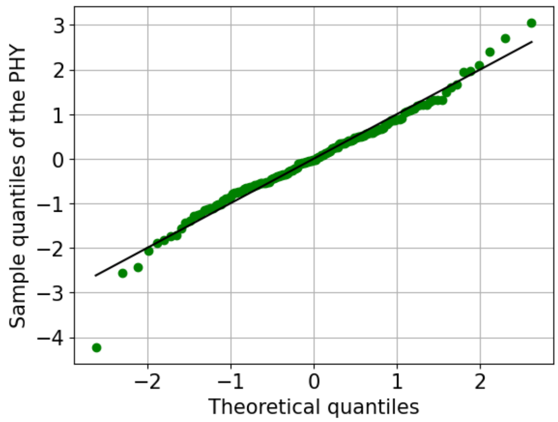
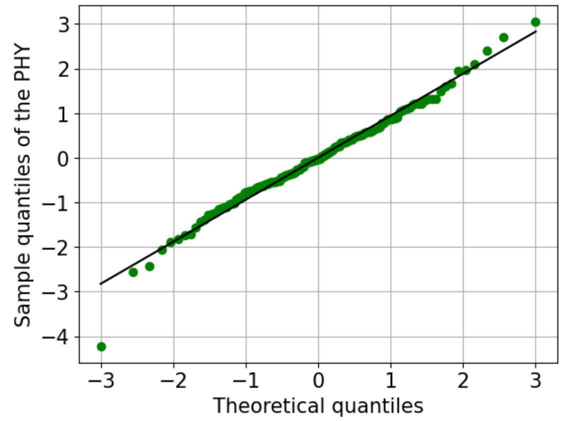


Figure E.1: Residual analysis with the normal distribution

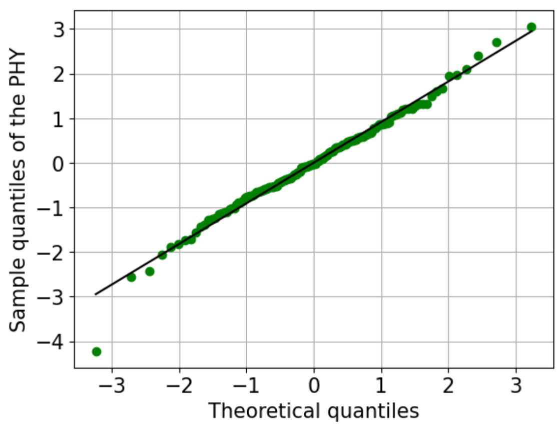
E.2 Risk factors fit: Q-Q plots



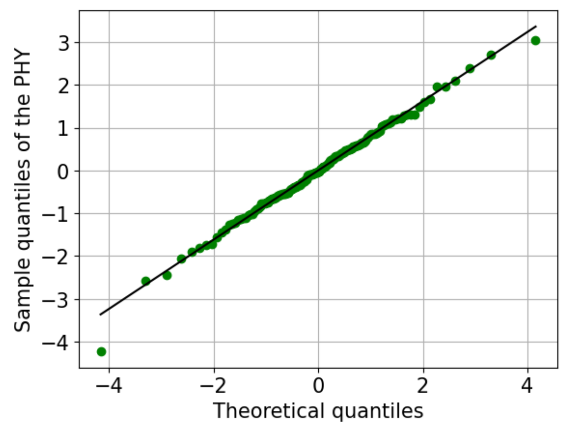
(a) PHY against normal distribution



(b) PHY against student t-distribution with 15 degrees of freedom

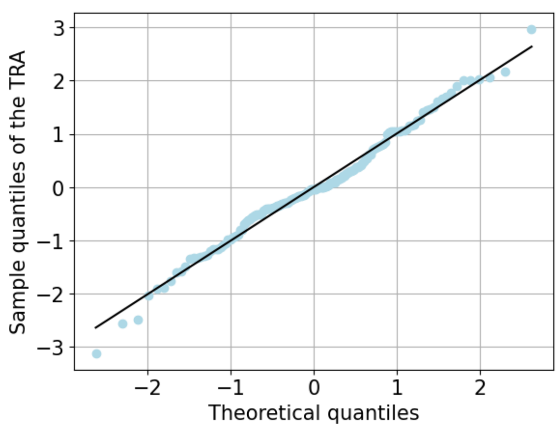


(c) PHY against student t-distribution with 10 degrees of freedom

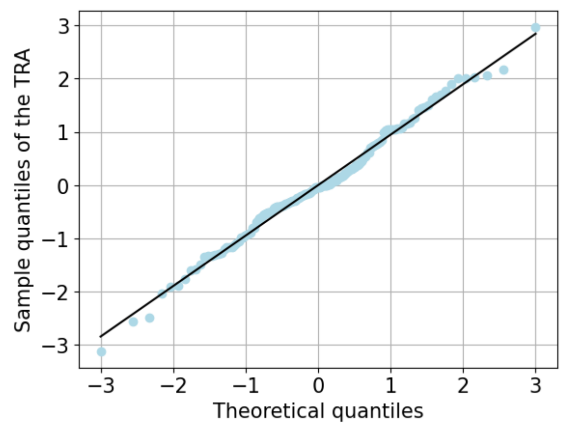


(d) PHY against student t-distribution with 5 degrees of freedom

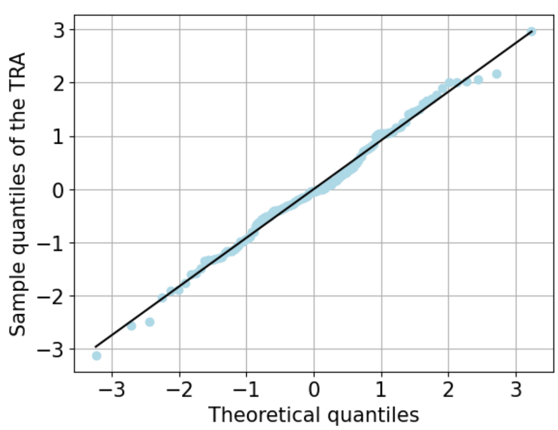
Figure E.2: PHY analysis with different distributions



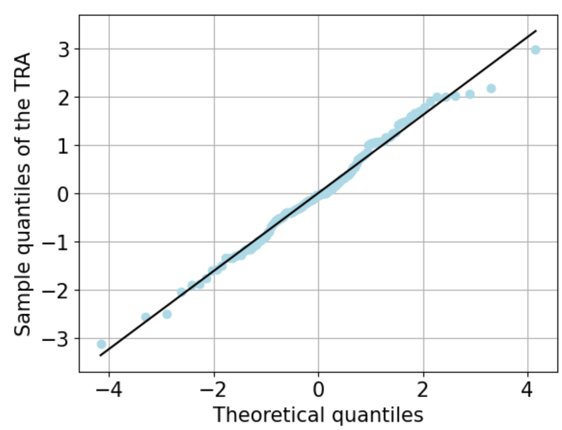
(a) TRA against normal distribution



(b) TRA against student t-distribution with 15 degrees of freedom

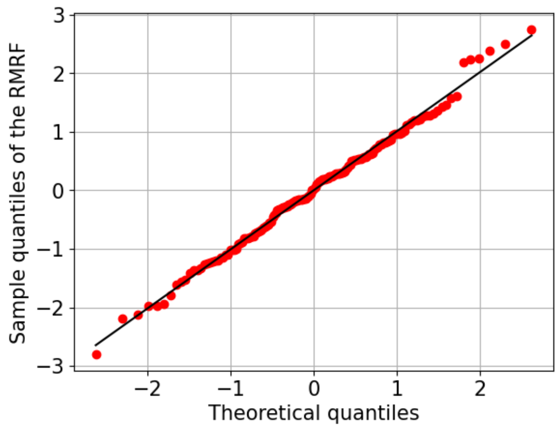


(c) TRA against student t-distribution with 10 degrees of freedom

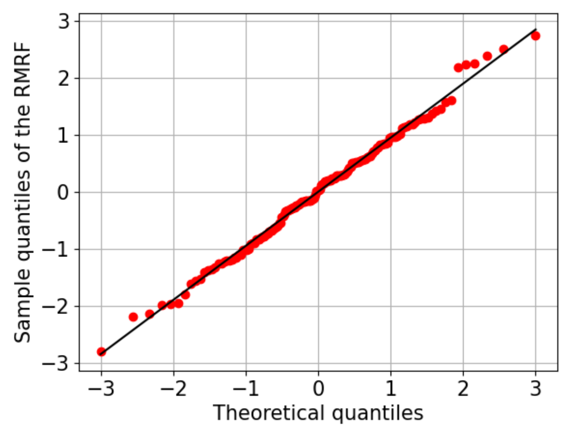


(d) TRA against student t-distribution with 5 degrees of freedom

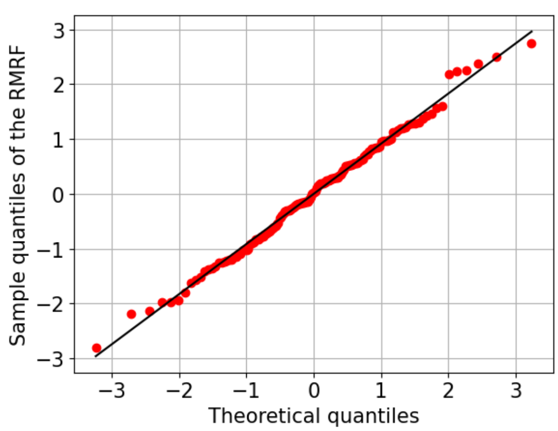
Figure E.3: TRA analysis with different distributions



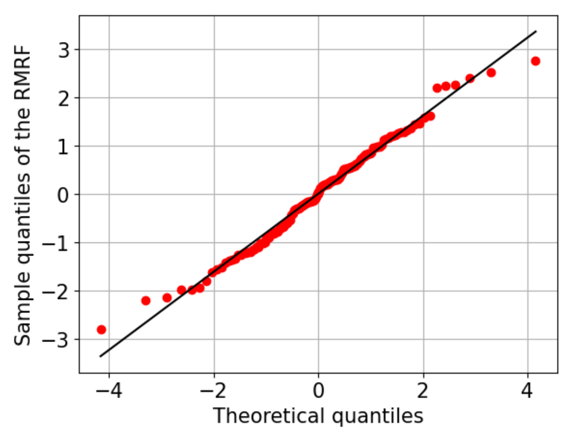
(a) RMRF against normal distribution



(b) RMRF against student t-distribution with 15 degrees of freedom

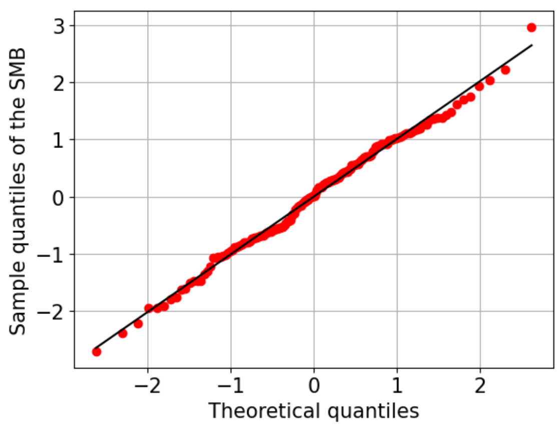


(c) RMRF against student t-distribution with 10 degrees of freedom

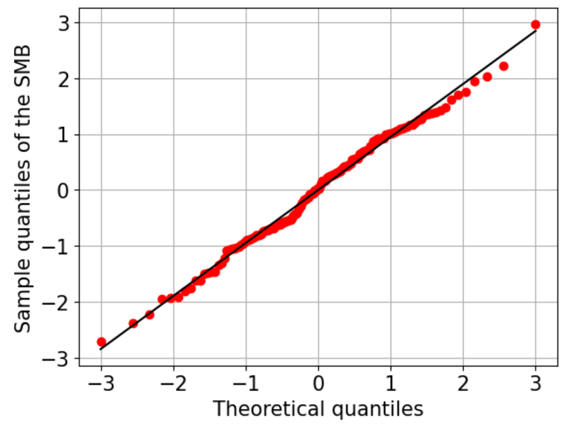


(d) RMRF against student t-distribution with 5 degrees of freedom

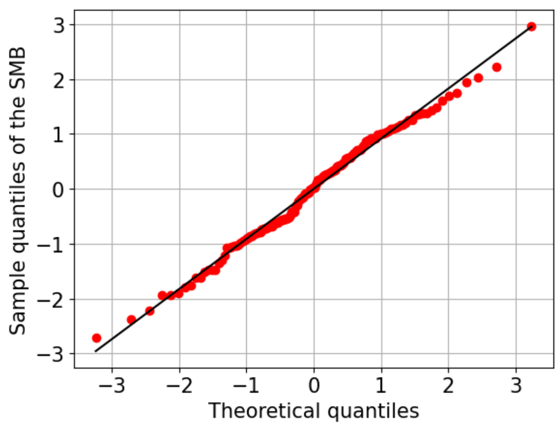
Figure E.4: RMRF analysis with different distributions



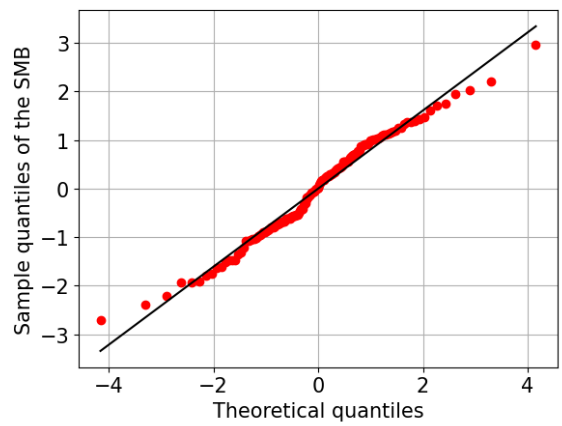
(a) SMB against normal distribution



(b) SMB against student t-distribution with 15 degrees of freedom

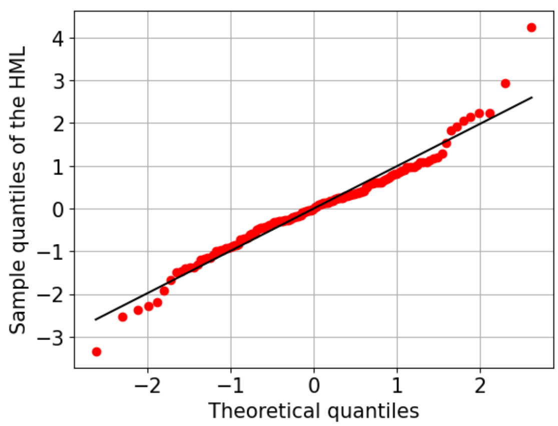


(c) SMB against student t-distribution with 10 degrees of freedom

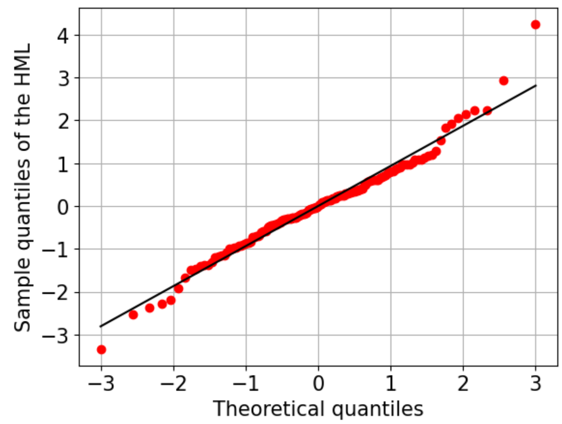


(d) SMB against student t-distribution with 5 degrees of freedom

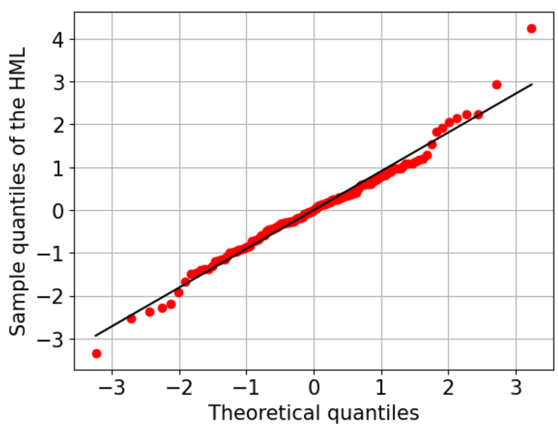
Figure E.5: SMB analysis with different distributions



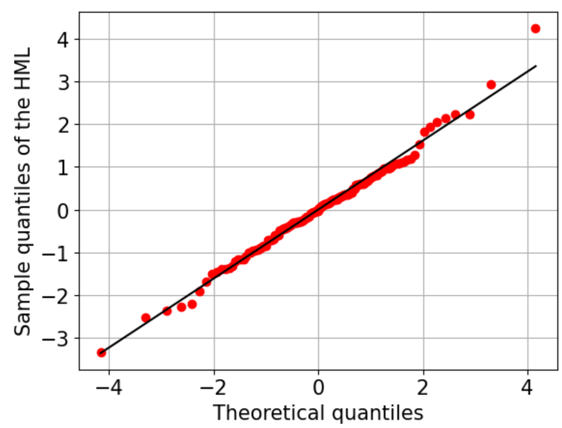
(a) HML against normal distribution



(b) HML against student t-distribution with 15 degrees of freedom

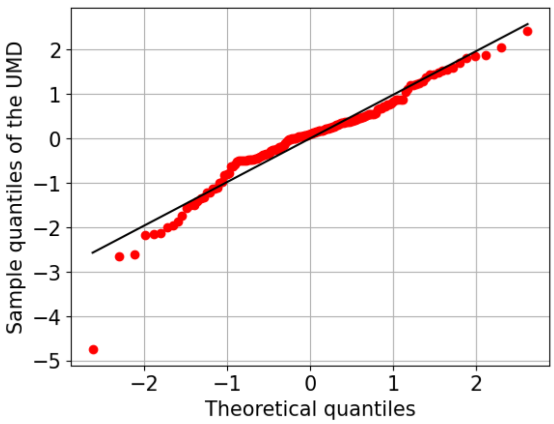


(c) HML against student t-distribution with 10 degrees of freedom

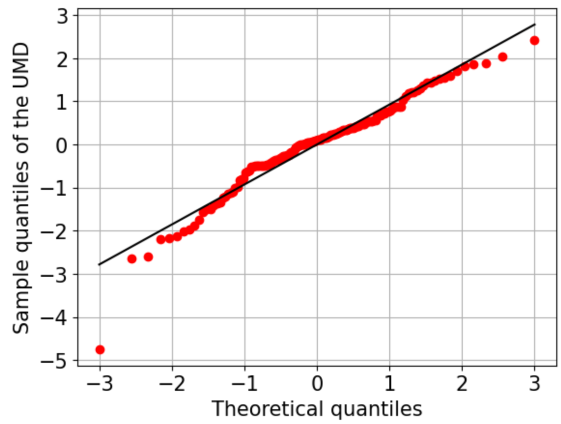


(d) HML against student t-distribution with 5 degrees of freedom

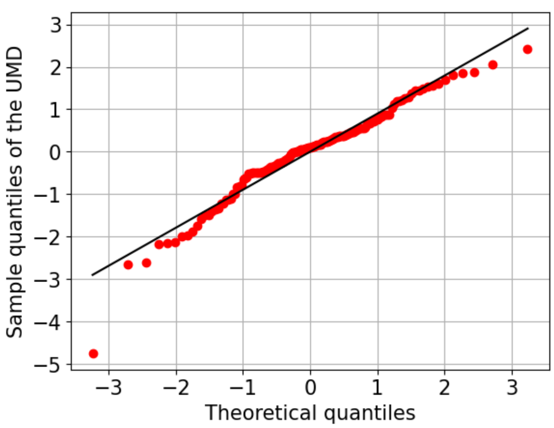
Figure E.6: HML analysis with different distributions



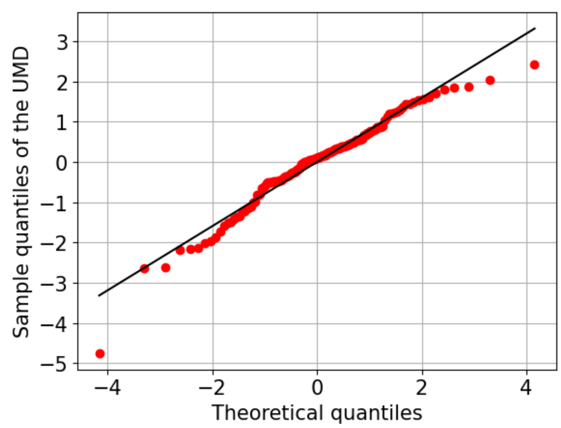
(a) UMD against normal distribution



(b) UMD against student t-distribution with 15 degrees of freedom



(c) UMD against student t-distribution with 10 degrees of freedom



(d) UMD against student t-distribution with 5 degrees of freedom

Figure E.7: UMD analysis with different distributions