
MOTIVATION OF COMPANIES TO JOIN CLIMATE ACTION & AN AGENT-BASED MODELLING APPROACH

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Executive Summary

The conclusion of Paris Agreement (2015) gave rise to many international climate initiatives. The Science-Based Targets initiative (SBTi) is one of the most predominant ones and is rapidly increasing its membership both in commitments but also in submissions of emission reduction targets.

This thesis uses pre-existing theoretical frameworks that focused on SBTi or more broadly on climate action to develop an agent-based model that explores factors which were found in previous studies to influence the companies' decision to join SBTi or climate action in general.

The model simulates the process for CDP (formerly the Carbon Disclosure Project) high-impact companies to set an SBTi target through four states: unaware of the existence of SBTi, aware, committed, and having a target. The transitions are shaped by three processes: the awareness process, commitment process, and target setting process, influenced by a company's combination of culture dimensions, country of origin and sector. These characteristics are used to calculate motivation and pressure which in turn are used for a company to commit or set a target.

The model findings on sectoral characteristics suggested that high-impact companies non-manufacturing sectors such as Financial Services and Transportation services are more likely to commit or set an SBTi target while manufacturing sectors tend to score lower. The model predicts such a pattern however the existing SBTi report does not show such a clear pattern indicating that even though the model captures the general trend, other dynamics such as regulations or economic factors which are not included in the simulations, influence the commitment and set target rates.

Regarding country characteristics, the cultural mapping tool by Erin Meyer was used to make propositions as to which dimension affects what part of the decision-making. The model suggested that companies from countries with 1) more straightforward communicating norms; 2) direct negative evaluation behaviours; 3) are more confrontational; 4) that base their trust on personal contact; 5) favour stricter deadlines and 6) have a more egalitarian power structure are more likely to commit and set targets with the SBTi. The deciding dimension showed ambivalence in committing and setting targets, with more consensual cultures more likely to commit while more top-down cultures more likely to submit a target, possibly due to a faster decision-making process as not everyone needs to agree.

Comparing the outcomes to the existing numbers of commitments and set targets with the model outcomes, there was a high Pearson correlation suggesting that the model does capture the broad trends of how culture affects decision-making.

The model also incorporates specific scenarios to test what approaches would lead to higher commitment and set target rates by 2025. This was done inspired by the existing shareholder campaign run in collaboration between CDP and SBTi focusing on this high-impact group. Increased market pressures and manager

pressures led to a higher commitment and set target rates than the shareholder campaigns, while the combination of those pressures lead to even higher commitments and targets. This increase seems to be limited at higher percentages due to specific companies in the model having very unfavourable scores on Deciding and Scheduling dimensions.

The simplicity of the model and the fact that several dimensions like regulatory and economic aspects are not included in the model does not allow for conclusive recommendations on the strategies that the SBTi should develop, however it is clear that a combination of campaigns focusing not only on shareholders but also on pressures between companies (market pressure) or internal pressures coming from the employees and the top-management could hasten the progress of the SBTi. Based on the strong correlations found between culture characteristics and likelihood in joining, it is also recommended that more focus should be put in the specific location of these companies to understand their needs and limitations and what could ease their involvement in climate action.

The model is developed in a field with large epistemic uncertainty with concepts such as pressures and motivations being often used to describe similar trends. Furthermore, the lack of openly-available data which leads to many assumptions and limitations on the insights that can be taken from it. Future research should focus on a more systematic data collection on companies that accept to have their data publicly disclosed. A more comprehensive model that takes into consideration environmental and regulatory factors could provide a more realistic reflection of the climate private governance arena.

Beyond its limitations, this model is one of the first ABM models used to explore the corporate motivations and pressures. The use of the culture dimension framework was also an innovation that gave some promising results indicating that such a framework could be used to understand organisational and corporate culture.

Chapter 1

Introduction

1.1 Motivation

Climate change is now understood by the international community as an urgent threat to the survival of humankind. The global agreement on the urgency for action, has led to the creation of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992, an international environmental treaty, in an effort to develop cooperation among all states. Its decision-making body, the Conference of Parties have been meeting annually to assess the progress of climate action (United Nations Framework Convention on Climate Change, [n.d.](#)).

In this international dialogue, it was universally acknowledged that ‘holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels’ (Paris Agreement, [2016](#), Article 2.1) is the overarching aim of the UNFCCC. According to the latest Intergovernmental Panel on Climate Change report ([2023](#)), the temperature increase is currently at 1.1°C above pre-industrial levels. The first implementation of measures under the UNFCCC was the Kyoto Protocol which was signed in 1997 and came into force in 2005. This first effort was deemed a top-down approach that mandated legally binding emission targets (Widerberg & Pattberg, [2015](#)). The U.S. refused to ratify it in part because there were no limits imposed on China. The effort of a top-down global governance met a backlash rooting to national interests. The conclusion of the Copenhagen Summit 2009 indicated that the “targets and timetable” approach should be reconsidered.

This led to a shift towards a “pledge and review” approach and an inversion from the top-down Kyoto Protocol to the bottom-up Paris Agreement in [2016](#). According to Article 4 “[e]ach Party shall prepare, communicate and maintain successive nationally determined contributions [“NDCs”] that it intends to achieve” (Kyoto Protocol, Article 4). Thus, if a Party (State) fails to deliver its goals, it does not get penalised. The flexibility of the Paris Agreement achieved what its predecessor, the Kyoto Protocol did not: the biggest emitters signed the agreement. However, without mandatory emissions targets, the pledges submitted lack ambition in total-

the Parties' current pledges "put the world on track for around 2.5°C of warming by the end of the century according to the recent report by UNFCCC (United Nations Framework Convention on Climate Change, 2022).

Amidst this new development in the political arena, the shifting away from the admittedly failed attempts of a global top-down climate governance towards more diffused governance arrangements, the concept of private climate governance and the International Cooperative Initiatives (ICIs) emerged (UNEP, 2018; Widerberg and Pattberg, 2015). Due to the bottom-up character of the Paris Agreement, non-state (e.g. businesses) and subnational (e.g. cities, states, and regions) actors (NSAs) have been recognized as key contributors for the reduction of greenhouse gas emissions. Simply put, the ICIs "are multi-stakeholder arrangements where NSAs work together across borders, often with national governments and other international organizations" (Lui et al., 2021).

This project's objective is to provide insights on how companies end up joining the ICI Science Based Target initiative (SBTi), which aims to help companies set emission reduction targets in line with climate science and its potential in increasing its membership and the ambition of its members to commit and accomplish 1.5°C, 2°C and net-zero targets. The SBTi has developed two target-setting methods for scope 1 and scope 2 emissions: a) The absolute contraction approach that 'implies that all companies reduce absolute emissions by the same proportion' (Bjørn et al., 2022) and b) the sectoral decarbonization approach which takes into account that some sectors due to less cost of mitigation will reduce emissions faster while also includes growth projections of each sector. This second methodology is becoming available in homogeneous sectors such as steel, cement and aviation (Initiative, 2015).

The research method used is an agent-based model which simulates the evolution of the SBTi from its establishment in 2015 until 2025. A simulation approach has been used in various types of collective actions and could shed light on potential pro-environmental tipping points for collective agent action (Kaaronen & Strelkovskii, 2020). Within this methodology companies are understood as composite actors i.e. actors that encompass multiple individuals however are treated and perceived as unitary actors (Eslamizadeh et al., 2022) and thus can be modelled as agents that collectively affect the system and interact with each other resulting to emerging behavioural patterns. In this study, a model is built with the purpose of simulating how the membership of SBTi will evolve over time and what their potential significance can be in the effort of reducing emissions.

This chapter gives an overview of the research approach to model the development of the climate action in the private sector. In Section 1.2 the research problem and the knowledge gap are defined, the main research question and related sub-questions are presented and the methodology choices are justified. In Section 1.3 the thesis outline is presented in a research flow diagram.

1.2 Research Problem

1.2.1 Problem Statement & Knowledge Gap

As mentioned above, the role of companies and NSAs in orchestrating and leading climate actions has gained traction and academics have tried to assess the potential of this phenomenon under various headings including "private climate governance", "corporate collective action" to name a few. Studies, such as the qualitative study by Banda L. (2018) focused on specific private climate governance schemes and have shown promise. On the other hand, it has also been acknowledged that current company targets and pledges are not sufficient in order to reach the Paris Agreement targets (Hsu, 2016). Furthermore, studies have shown that corporate climate actions can end up in green washing practices and opportunistic behaviours due to the lack of transparency and their voluntary character.

The emergence of ICIs is an effort to provide credibility to the target setting of companies, transparency on the disclosure of emissions reduction and guidance for individual companies and other NSAs to act collectively and push for more ambitious goals. Some researchers have criticised their potential (Widerberg & Pattberg, 2015)(Hsu, 2016) especially at the initial stages for this emergence. Since then, many studies have shed light on ICIs' potential to be the bridging apparatus between the Paris Agreement on GHG emissions reduction targets and nationally determined contributions (efforts by each country to reduce national emissions and adapt to the impacts of climate change) (Bolton & Kacperczyk, 2022), (Kuramochi et al., 2020), (Lui et al., 2021).

This thesis focuses on one prominent and rapidly growing ICI, the Science Based Targets initiative which arose from the collaboration of the World Resources Institute, the World Wide Fund for Nature, the UN Global Compact and CDP (previously known as Carbon Disclosure Project). The SBTi provides guidance for the companies depending on their sector to set emission reduction targets that align with the science-based targets that have been agreed upon in the Paris Agreement- namely targets that lead to a global warming restriction either below 2°C and 1.5°C. As of November 2022, 4061 companies have taken action (either commitment in setting a target or have an approved science-based target by SBTi) and 1957 have already approved science-based targets. The SBTi has finalised the guidance for a number of sectors such as steel, aviation, forest, land and agriculture and plans in completing and revisit several others like cement. By the end of 2021, 27 % of the high-impact companies globally, work with SBTi (SBTi, 2022). The SBTi Progress report, found that companies with approved SBTs have reduced scope 1 and 2 emissions at a rate higher than what is globally required to meet the target of 1.5 °C. Following the 'diffusion of innovations' theory, that proposes that if 10-25% of companies adopt an innovation, a rapid adoption from the remaining members takes place, SBTi takes the threshold of 20% to be the potential 'tipping point' (Science Based Targets initiative, 2021).

This promising development led several studies in the recent years to focus on SBTi with some interesting findings. Kuo and Chang (2021), found a strong correlation between SBT adoption and CDP score (i.e. the more environmentally responsible companies are more likely to join SBTi) and that high carbon emitting industries that adopted both SBTs and internal carbon pricing get a better CDP score than those that did not. According to the recent Bolton and Kacperczyk (2022) statistical analysis study which focused on CDP and SBTi initiatives, companies are more likely to set SBTs if they are larger, have lower emissions and already disclose their emissions. They also concluded that these target setting initiative were successful in attracting companies that are already willing and able to reduce emissions but faced greater resistance from companies in sectors that need to reduce their emissions the most. In another empirical study by Freiberg et al. (2021), the findings showed that companies are more likely to set SBTs if they set and achieved ambitious carbon target in the past, if they perceive climate change-related risks as economic risk to their business, and if they have carbon-intensive operation. They also concluded that companies set more challenging targets and invest more in emission reduction after adopting SBTs.

The conclusion of the literature review done by (Bjørn et al., 2022) regarding the existing studies that focused on SBTi is that a diversity of approaches is needed to better understand the dynamics that influence the decision-making of companies.

The aim of this thesis is to explore how several factors that have been identified by previous studies interact. In the complex private governance arena, all these factors coexist and influence the companies, while companies also influence each other. This dynamic interdependence of several factors represents a knowledge gap in the existing literature, and this thesis aims to address that gap by exploring how these factors interact within the complex landscape of private governance.

1.2.2 Research Goal and Scope

The goal of this project is to examine what factors or combinations of factors will possibly increase or decrease the commitment of the SBTs. There are multiple scales of analysis that influence the evolution of the SBTi— the individual company with its specific interests and capacities; the decisions taken by the SBTi that will influence its uptake and the external policies that affect the environment of all these interactions. Thus, the sphere in which SBTi operates can be perceived as a complex adaptive system. According to Nikolic and Ghorbani, 2011, the complex system theory assumes that the system's behavior as a whole can be explained 'by the decisions made at every moment by every individual within that system' (p.44).

The research scope is centered on the motivations and pressures of CDP high-impact companies to join the SBTi. The study specifically delves into the strategies and campaigns of the SBTi targeted at these companies and explores the broader motivations for companies to engage in climate action. The broad scope on all high-impact companies as identified in a collaboration of SBTi and CDP, including all sectors and countries, is decided in order to give insights on higher level processes.

1.2.3 Research Questions

Following the elaboration of the research goal, the proposed main research question is:

“Why do companies join SBTi?”

The answer to this question will focus on the following sub-questions:

1. What are the existing strategies and campaigns of SBTi to incentivize high-impact companies to commit and set science-based targets?
2. What are the current motivations for companies to join climate action according to previous research?
3. What are the current stakeholder pressures that incentivize climate action according to previous research?
4. What are the factors that have been identified as related to companies joining SBTi from existing research?
5. How does the combination of these factors (questions above) affect the uptake of companies?
6. What are potential strategies that SBTi can implement to speed its uptake?

1.2.4 Research Method and Design

In order to answer these questions, this project will use a computational model. There are three reasons why this is chosen. The emergence of ICIs is a complex dynamic phenomenon that involves polycentric multi-level governance and interaction between physical, social and technological dimensions; the outcomes are very complex and interwoven to calculate, and difficult to anticipate any emergent consequences on the basis of common sense or empirical knowledge (Calder et al., 2018). Furthermore, computational modelling can give insights on underlying mechanisms that play a role in possible future outcomes. Finally, a computational method facilitates a study of several possible future scenarios since variables in question can be varied and a high number of experiments can be run in a short time.

From the variety of possible computational models, the agent-based modelling (ABM) method has been chosen. There are several advantages of this method that align well with the system under study. Firstly, ABM has the capacity to represent entities, such as companies, as agents with diverse attributes and allows flexibility in their decision-making. This approach allows discovering emergent patterns from a bottom-up perspective (Nikolic & Ghorbani, 2011). Moreover, ABM modeling recognizes that reality is made up of numerous components operating at the same time. It characterizes these components and allows them to engage with each other in real-time, capturing a broad spectrum of potential interactions. Rather than striving for a specific state or goal, it focuses on exploring the various possible states of the system. The exploratory nature of ABM is ideal for systems with limited clarity. The system analyzed in this report analyses motivations and pressures for companies, rooted deeply in a social reality that’s challenging to

validate and hence ABM was deemed the right choice. Lastly, ABM is a method that has not yet been used in studies relevant to SBTi, and an initial ABM model could provide a promising beginning in shedding light on new dynamics and offering alternative perspectives for future research endeavors.

Drawing from the guidelines laid out by Nikolic and Ghorbani, 2011, the process of creating the ABM for this study followed a structured approach consisting of 5 iterative steps:

System Analysis: This initial step can be broken down into two sub-steps:

1. **Problem Identification:** This is detailed in this chapter which includes the problem statement, the research goals, the research scope and the research questions. In short, the model focuses on the motivations and pressures of CDP high-impact companies to join the SBTi.
2. **System Identification:** The Theoretical Underpinning (Chapter 2) delves into this aspect. It identifies the theoretical frameworks employed to elucidate the motivations and pressures on companies in joining climate action, and where possible specifically joining the SBTi. The chapter further expounds on the SBTi's targeted strategies and promotional campaigns, giving more detailed information about the scope of the study around the CDP High-impact companies sample.

Conceptualisation and Formalisation: In this step (Chapter 3), the identified entities and dynamics are conceptualized into a structured framework, detailing how different components interact and influence each other. This phase sets the foundation for how the model will operate. The companies are conceptualised as the agents of the model that interact with each other to become aware about the existence of the SBTi or to create pressures in committing to their neighbours. The theoretical foundation is then translated into mathematical formulations, variables and parameters.

Verification and Validation: This step (referenced in Chapter 4) is critical to guarantee the model's reliability and to ensure that its representation aligns with reality. It involved a series of tests to confirm that the model operates as designed. Sensitivity analysis methods were used here to evaluate how changes in input parameters influence the model's results and verifying its resilience. Moreover, the sensitivity analysis identified the parameters with the most significant impact on outcomes. The most significant parameters were then tuned to ensure that the model's average results aligned with the actual SBTi uptake figures for the period from May 2015 to May 2020. This timeframe encompasses the interval between the establishment of the SBTi and the beginning of the first CDP high-impact companies campaign.

Experimentation: The final step (Chapter 5) involved running a series of experiments for possible projections over the period 2015-2025. The first half of this timeframe (2015-2020) captures the historical progression since SBTi's establishment and the latter half (2020-2025) provides projections on the SBTi uptake. The relevance of our model is limited in temporal scope since it simulates a rapidly-evolving system, thus projections further in the future become less meaningful. The experiments simulate possible scenarios for

different campaigns/strategies that the SBTi can incorporate to increase the uptake of companies such as increase manager pressure, market pressure and employee pressure.

It has to be noted that this approach had multiple re-iterations and back and forths between the steps discussed above. However, the thesis presents the steps in a linear form with each step being a separate chapter. The thesis closes with a Discussion (Chapter 6 on the meaning of the results and Conclusions (Chapter 7) where the extent of how much the research questions were answered is discussed, the limitations faced presented and the scientific contribution and future research is elaborated.

1.2.5 Relevance for Industrial Ecology

Industrial Ecology is the “..the study of the flows of materials and energy in industrial and consumer activities, of the effects of those flows on the environment, and of the influences of economic, political, regulatory, and social factors on the flow, use, and transformation of resources” (White, 1994). This requires an understanding not only of the physical/technical dimension of a given problem but also its societal and economic dimension.

This study is concerned with the global problem of climate change and how the SBTi could contribute in the reduction of the global flow of greenhouse gases by guiding the corporate climate action. The use of a model to determine which factors, already identified in the limited academic literature on SBTi, weigh more in the corporate decision to participate and set targets can illuminate which policies or executional SBTi decisions can speed the uptake.

Industrial Ecology represents a multidimensional field of study. It concerns the “flows of materials and energy in industrial and consumer activities, the effects of these flows on the environment, and the myriad factors—including economic, political, regulatory, and social—that influence the use and transformation of resources” (White, 1994). Such a definition underscores the importance of understanding a challenge not only from the physical and technical dimensions but also from its societal and economic dimension.

In the context of this field, this study delves into the pressing global problem of climate change, specifically examining the role of the SBTi in guiding companies to reduce greenhouse gas emissions. The use of a model to explore the determinants that influence corporate participation in the SBTi—a topic with limited existing academic literature—can illuminate which policies or executional SBTi decisions can speed the uptake. Previous findings have shown that the success of SBTi uptake is linked with the environmental flows associated with greenhouse emissions.

1.3 Thesis Outline

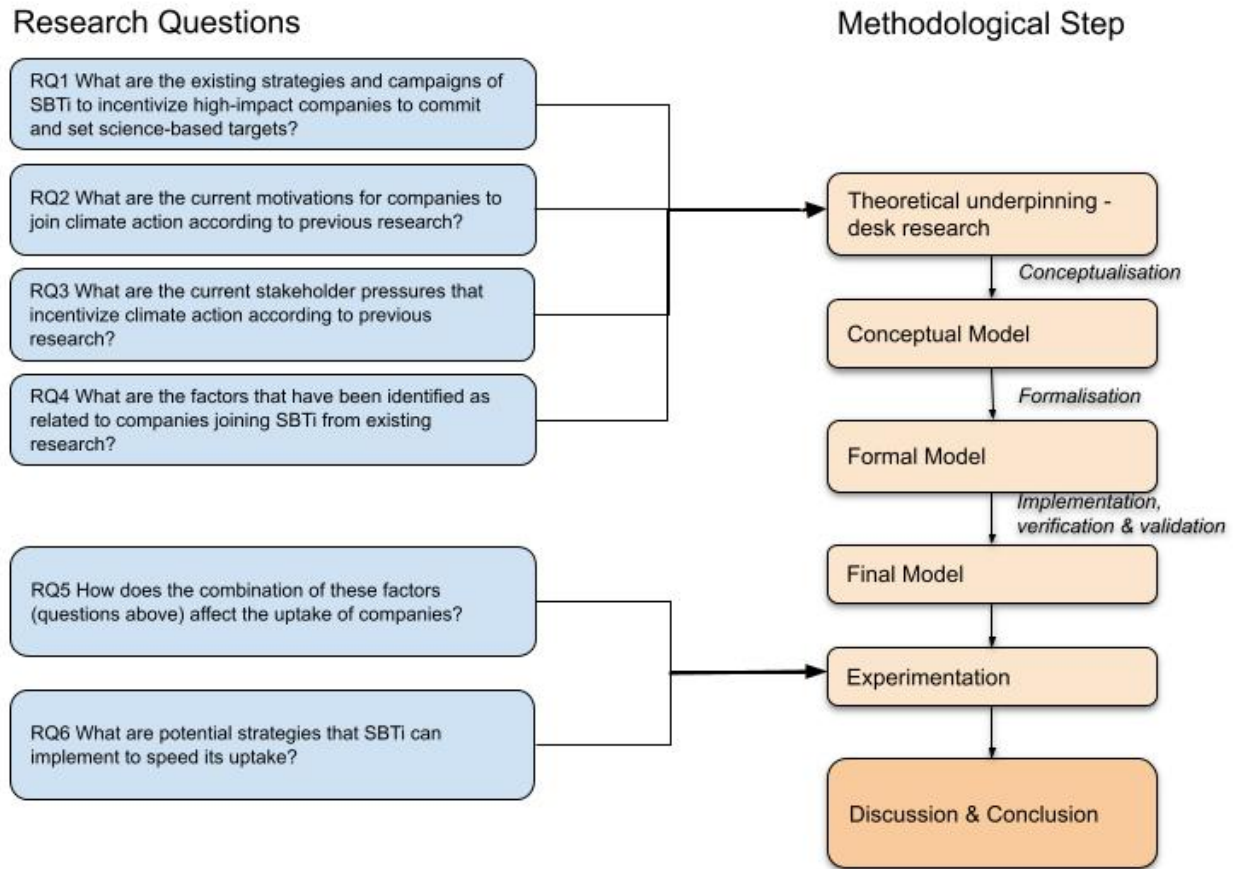


Figure 1.1: Estimated timeline

Chapter 2

Theoretical Underpinning

This chapter is divided into three main sections. The first section provides a brief background that led to the emergence of private climate governance and the establishment of international cooperative initiatives and specifically the Science-Based Targets initiative (SBTi). The second part of the first section provides a closer look at the case of SBTi and answers sub-question 1- "What are the existing strategies and campaigns of SBTi to incentivize high-impact companies to commit and set science-based targets?". The second section provides a brief summary of the existing research on companies' motivations and pressures towards climate action and any existing empirical findings about SBTi, answering the sub-questions 2,3, and 4. The third section describes the combination of the theoretical frameworks used to explain corporate motivations and stakeholder pressures towards climate action that will be used in the conceptualisation and formalisation of the model in Chapter 3 and the incorporation of Erin Meyer's Culture map (Meyer, [2014](#)) to distinguish between different organizational cultures.

2.1 Case Background

2.1.1 The emergence of private climate governance and International Cooperative Initiatives

The traditional top-down governance schemes based on the law enforcement power of nation-states that were dominant for most of the 20th century started giving way to polycentric governance schemes in the mid-1970s. This transition brought various (Bakhtiari, [2018](#)) non-state actors such as companies, NGOs and municipalities into the political arena. This led to the involvement of non-state actors and transnational networks in international environmental politics by the 1990s (Banda, [2018](#)).

Examples of non-state authority organisations such as the well-cited Forestry Stewardship Council (FSC) founded in 1993, have attracted political and academic interest (Cashore et al., [2004](#)). This led to several governance models and research focusing on multi-level and polycentric governance.

According to Vandenberg [2013](#), private climate governance “occurs when nongovernmental entities take actions that achieve traditionally governmental ends concerning environmental protection or natural resources”. It has to also be noted that not every private-led climate action falls under the concept of private climate governance. Banda ([2018](#)) further clarifies that there are four features that are necessary to consider a scheme as private climate governance: a) it must not be government-orchestrated or managed i.e. not driven from a government regulatory command but initiated by private actors; b) it should not just seek private benefits but to change actor behaviour; c) the participation should be voluntary; d) it should exhibit some degree of coordination between actors.

Furthermore, the objective of private climate governance is not limited to reducing private actors’ GHG emissions but also to influencing the state’s behaviour (Banda, [2018](#))(see figure 2.1). Private governance assumes a dynamic understanding of the interaction between the state and NSA for climate change mitigation.

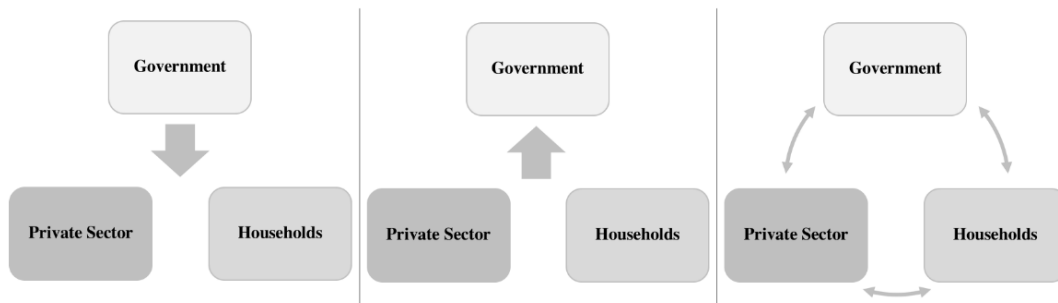


Figure 2.1: Governance Models: Top-Down, Bottom-Up, and Dynamic Governance (Taken from Banda, [2018](#), p. 27).

A sub-set of NSA actions, the International Cooperative Initiatives (ICIs) has an international scope, consisting of coalitions of governments and sub/non-state actors (Bakhtiari, [2018](#)). This scaling-up to entities with a multitude of actors and an international scope is an effort based on this dynamic understanding of the new governance schemes.

The SBTi is an example of an ICI which offers guidance specifically to companies. It has risen to prominence in recent years, reaching 70 countries and covering 35% of market capitalization (38 trillion dollars) by the end of 2021 (SBTi, [2022](#)). The SBTi reported in their progress report in [2022](#) that companies that have set SBTi approved targets have achieved larger reductions in carbon emissions. They acknowledge that their analysis does not take into consideration several factors that might lead to their results such as the representation of industries in SBTi or potential double-counting from parent companies and subsidiaries to name a few. An outlook of the SBTi and its strategies in increasing its impact by increasing its uptake on high-impact companies, as identified by the CDP, forms the basis of the next section.

2.1.2 The Science-Based Target Initiative (SBTi) and its strategy

Launched in 2015, the SBTi was established at the same time as the conclusion of the Paris Agreement discussions and quickly gained prominence in the field of corporate climate action (Bjørn et al., 2022). As an international platform, the SBTi offers guidance and a standardised framework for companies to set science-based emissions reduction targets. The initiative is a collaboration between CDP, the United Nations Global Compact, World Resources Institute (WRI) and the World Wide Fund for Nature (WWF) and aims to enable companies to achieve net-zero targets by 2050.

The 'science-based targets' (SBTs) that the SBTi promotes, were introduced in the science-policy discourse following the Paris Agreement, aiming to clarify the global warming limit as below 2°C above pre-industrial levels and the strive towards a 1.5°C limit (Andersen et al., 2020). According to Andersen et al., 2020, a science-based target is: a) feasible within a given time frame based on analytical evidence, b) quantifiable and with measurable progress towards achieving it, c) analytically justifiable for the target choice.

Aims

More specifically, the SBTi aims to mobilise the private sector towards climate action by:

1. Defining best practices in each sector
2. Providing technical assistance and expert resources during the target-setting process
3. Independently assessing and validate those targets
4. Promoting the Corporate Net-zero Standard which is a set of guidelines provided by the Science-Based Targets initiative (SBTi) for businesses to achieve carbon neutrality and align with global climate goals.
5. Increasing the accountability and credibility of corporate climate action through the future monitoring, reporting and verification framework.

5-step target-setting process

The process for a company to set an SBTi-approved target is broken into five steps (SBTi, n.d.-a):



COMMIT - The first step is to register online and submit a letter of commitment. Companies can either commit that they will set a target or just have their internal existing targets verified. Once committed, the companies are given 24 months to submit their targets to the SBTi.



DEVELOP - The companies then have to develop emission reduction targets that adhere to SBTi criteria. While SBTi offers general guidelines and recommendations, sector-specific guidelines have also been created for many industries to aid in target formulation.



SUBMIT - The emission reduction target(s) are then submitted for validation. The validation cost varies depending on the target type and company size.



COMMUNICATE - After expert review, if the target receives SBTi approval, it will be published on the SBTi platform. The companies must make their target public within six months.



DISCLOSE - The company should then disclose emissions annually in order to monitor the progress towards the SBTi target.

2.1.3 Strategies to incentivize high-impact companies to join

CDP climate high-impact Campaign

CDP is an international, not-for-profit organization that assists companies to measure and disclose their environmental impact using a variety of environmental metrics. The CDP annual survey is considered the most comprehensive source of cross-sectional data on emission reduction targets by companies (Freiberg et al., 2021). It is one of the founding organisation of the SBTi.

CDP has created a sample of 2237 companies in 2019 (SBTi, 2022), called the CDP high-impact sample (CHIS), which represent the most significant companies in terms of market capitalization and GHG emissions (CDP, n.d.). Their total market capitalization is around 67 trillion dollars, while their emissions are equivalent to the combined emissions of EU and USA (SBTi, 2022).

The criteria used to select these companies are the following (taken from CDP, n.d.):

1. Companies with the highest scope 1, 2, and 3 GHG emissions (>80th percentile of the total CDP company sample).
2. MSCI All Country World-index (ACWI) constituents with the highest market capitalisation (>85th percentile of the total MSCI ACWI sample). MSCI ACWI is a stock index that tracks broad global equity-market performance. Market capitalization is calculated by multiplying the company's total number of outstanding shares by its current stock price.
3. Companies that satisfy the following two criteria:
 - (a) Among the highest market capitalization in the country where its headquarters are located, compared to other companies in the same country (>85th percentile by country). This is taken from the CDP investor sample.

- (b) Among the highest GHG emissions for its industry (>85th percentile by sector - GICS) or above 70th percentile of the whole CDP sample.

4. The 20 largest private US companies and the 15 largest private EU companies by revenue

CHIS serves as the foundation for smaller targeted samples used in the CDP's annual SBT Campaigns. These campaigns have run for three consecutive years:

- In 2020, the target sample was 1830 companies. The exclusion criteria were:
 - Companies outside the investable universe
 - Companies not requested by investors to disclose to CDP
 - Companies committed to SBTi
- In 2021, the target sample was 1616 companies and the exclusion criteria were:
 - Companies committed to SBTi
 - Companies whose market status changed in the last year (e.g., acquired or merged). This included companies acquired by or merged with those committed to SBTi and companies that ceased operations.
- In 2022, the target sample was 1061 companies and the exclusion criteria were:
 - Previous criteria mentioned.
 - Companies unable to commit to SBTi due to the current policy on fossil fuel companies.
 - Companies with headquarters in Russia or Belarus (paused commitment by SBTi).

The campaigns try to use the support of global financial institutions to attract high-impact companies to commit. The financial institutions represent the biggest capital markets signatories (shareholders), thus can provide shareholder pressure towards significant companies to align their targets with the SBTs. In the 2021-2022 campaign, the financial institutions involved had combined assets of almost \$30 trillion.

According to the last annual progress report of SBTi, as of December 2021 598 high-impact companies have become members- 212 with commitments and 386 already turned their commitment into approved targets. (SBTi, 2022). The SBTi report also provides a breakdown of high-company uptake in each continent (figure 2.2), sector (figure 2.3) and country (SBTi, 2022, p. 23-24). The high-impact companies are mostly concentrated in Europe, Asia and North America with largest representations in the US (533 companies), China and Japan (230 each). One out of two European high-impact companies have committed to SBTi in comparison to 1 out of 9 African and 1 out of 8 Asian ones. This indicates an uneven geographical expansion of the SBTi. The sector commitment and set target percentages present a very uneven image which might indicate the difficulty of some sectors to adhere to the SBTi guidelines.

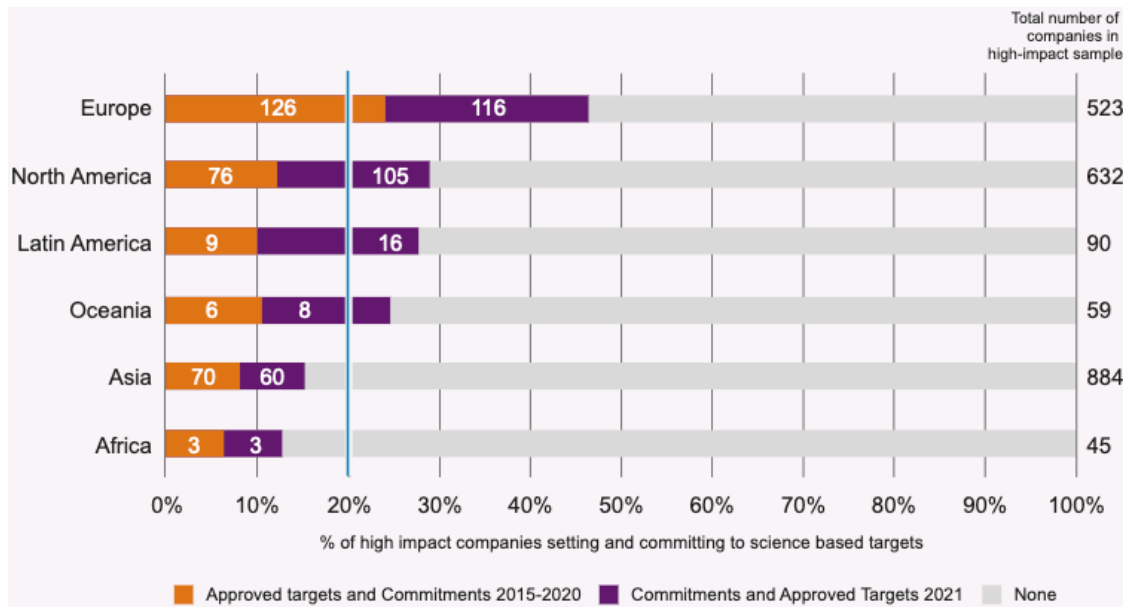


Figure 2.2: High-impact companies' commitments and approved targets by continent as of December 31 2021. (Taken from SBTi, 2022, p. 22).

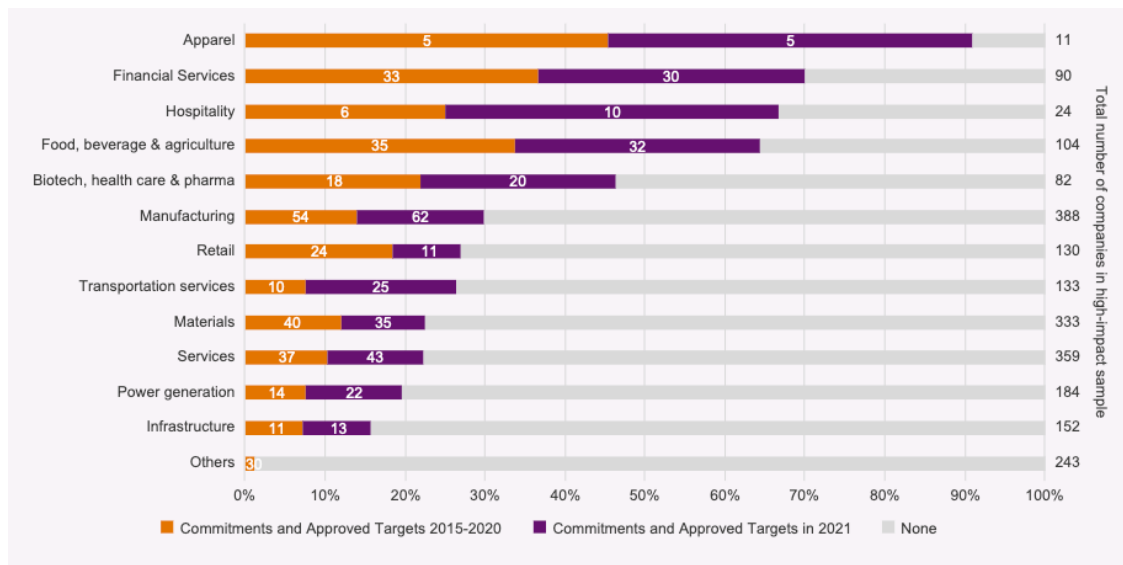


Figure 2.3: High-impact companies' commitments and approved targets by sector as of December 31 2021. (Taken from SBTi, 2022, p. 25).

2.2 Companies' motivations and stakeholder pressures

2.2.1 Motivations of companies to join the climate action

As previously discussed, the new evolving political reality has created space in the climate action arena for companies to become subjects more directly involved in this global socio-economic transition. Consequently, an extensive body of literature rapidly has developed to reflect on what motivates companies towards climate

action. These studies explore the phenomenon from numerous perspectives and stemming from various disciplines and foundational theories.

Several frameworks have been created to categorize and analyse the reasons for companies voluntarily participating in GHG emission reductions. In order to navigate through this complex maze of concepts and fields, I follow the steps that van Hilten (2022) took in her master thesis project which also focused on SBTi. She used the systematization of motives developed by Windolph et al. (2014) who compared empirical findings on the implementation of sustainability management and clustered the motives around three concepts: Legitimacy, Market Success and Process Improvement. As Simões-Coelho and Figueira 2021 explain, this systematization does not follow the motivation literature rooted on individual needs and behavioural patterns i.e. drivers/motivations linked to individual and only through the individual to an organizational level. Such studies have analysed the importance of board constituency, CEO motives, influential executives etc (Lerner & Osgood, 2022), (Choo, 1996). Windolph et al. (2014) treat companies as a single entity and comprehends motivations as corporate motivations excluding personal ones. This choice is aligned to the thesis granularity where the simplest agent is the company (more in section 3.1.2).

The first category, legitimacy, has been a widely studied concept beyond corporate climate action. In relevant fields such as transition governance (Borrás & Edler, 2014) and political science, legitimacy was used to explain how organisations comply with institutions "adapting their practices and discourses to the evolving system of beliefs present in any society" (Simões-Coelho & Figueira, 2021). It is linked to sustainability management as companies need to comply with environmental and social regulations and laws, and private or self-regulations. Companies also need to consider stakeholder interests to secure access to critical resources such as workforce, capital, or the willingness to buy products and services. It is considered to be the corporate response to "institutional, legislative, or social forces and needs to be perceived as ethical by the public" (Simões-Coelho & Figueira, 2021). Overall, legitimacy is important for companies to ensure their long-term survival.

The second category is the market success. This encompasses several criteria such as increase in turnover, an entity's ability to compete in its market and continuous innovation to ensure continuity in success. As discussed in Section 2.1, companies' primary push towards climate action was regulatory factors in the 1990s. However, the market has also become a significant factor. Environmental and social considerations by companies have become a competitive advantage as customers and consumers demand companies to prioritize these aspects (van Hilten, 2022). Furthermore, market success has been studied in relation to company climate action and sustainable management and many studies have shown that sustainable management can improve "employee motivation with the company as well as employer attractiveness" (Windolph et al., 2014).

Finally, internal improvement refers to the reduction in resource usage and costs. It has been studied in relation to climate action since the optimization of processes not only improves the companies' profits but also leads to "eco-efficiency or socio-efficiency, i.e. the relation between a firm's value added (economic

dimension) and its environmental or social impact" (Windolph et al., 2014). Internal improvement towards sustainability involves improvement of and collaboration between different departments such as purchasing, logistics, production, finance, and accounting. Purchasing improvement could mean buying resources and products from responsible suppliers. Production can develop and implement energy-efficient and material-efficient processes. Logistics can assist in a more efficient reduction of waste and reuse of materials. Finance and accounting departments provide important information for investment decisions, price calculations, and sustainability reporting.

Two extra categories of motivations have been added more recently in an effort to cover the whole range of motives. According to Simões-Coelho and Figueira, 2021, the concept of Social Insurance is not adequately covered by the first three. It is the motivation to prevent potential losses and take preemptive measures to protect shareholders against financial risk. The distinction of it from legitimacy as explained by Simões-Coelho and Figueira, 2021 is that legitimacy is more focused on meeting the ethical expectations of stakeholders, while social insurance is more focused on financial protection and preservation of economic value.

The last category, organizational culture came as an addition by van Hilten, 2022 in an effort to include the personal motivations of board members, stakeholders from within the company. As explained above, the initial systematization did not include this dimension. The significance of culture in corporate sustainability success has been studied and there were indications that the decision-making of a corporate board or management is influenced by the individual behaviours, attitudes, expertise and society's norms. A notable proposition in the theoretical framework developed by Simões-Coelho and Figueira, 2021 based on a bibliometric study of a large number of articles on corporate sustainability and climate action was that these motivation categories are time dependent. Their findings indicated that companies early on in a system (a state or a region) are motivated by legitimacy due to the necessity to comply with regulations and process opportunities due to economic opportunities, while as the system progresses and sustainability becomes a significant aspect social insurance due to an more sophisticated awareness of the danger of climate risks and market success to gain shares in their sector become the main drivers. In short, early motivations for climate action are connected to compliance to institutions while later motivations are connected to "competition and differentiation" (Simões-Coelho and Figueira, 2021, p. 17). The progress of motivations' importance is a very insightful proposition, however it is not included in the scope of the model.

2.2.2 Empirical findings on the motivation of companies to join SBTi

This thesis is mainly drawing the findings of two previous master theses that focused on the motivations and drives for companies to join SBTi: van Hilten's 2022 and Fink's 2018.

Why corporates join the Science Based Targets initiative- Eva van Hilten

As mentioned in the previous section, van Hilten's updated corporate motivation framework was used in her master thesis to explore why corporates join the SBTi. She used a mixed-method study that entailed a statistical analysis (quantitative branch of her research) focusing on correlations of firm characteristics with SBTi participation and interviews that tried to analyze motives, reasons and drives to join (qualitative study).

In order to assess the categories of motivations discussed above, van Hilten has chosen specific proxies that were connected to each of these categories and tested her hypotheses on those proxies qualitatively through interviews and in most cases quantitatively too.

Regarding legitimacy, the proxies used were an analysis of which type of stakeholders' has the largest impact on the drive to participate in the SBTi and which sector types are more likely to participate. The stakeholder analysis showed that business clients and not end-consumers were more significant; this finding was repeated in Fink's thesis below. The sector analysis indicated that companies with less complex supply chains such as Information Technology are more likely to join and that energy companies that face policy risks don't necessarily have a higher likelihood to join. Market success was represented by employee size (larger companies) and intangible assets (innovativeness), both of which were found to contribute to an increase in the likelihood to join SBTi. The Social insurance category which is related to corporate risks was evaluated quantitatively based on if a company had a stand-alone risk committee and showed on direct link, however qualitative findings gave weight to social insurance's importance. The organizational culture was evaluated upon several proxies including board gender and culture diversity and leadership vision. In general, organizational culture was found to be significant regarding the SBTi.

The only category that was not backed up by its proxies or the interviews at all was the internal improvement which as explained before is concerned with the motivation to maximize efficiency. The quantitative analysis using as proxy the ownership of a Sigma Lean Six certificate, which indicates the company's endeavour in optimizing its process led to the opposite results. The qualitative study had the same conclusions with companies questioning whether a third party such as SBTi can offer technical knowledge and support.

2.2.3 What drives firms to successfully cooperate on climate change? - an institutional analysis of the Science Based Targets initiative- Lea Ottilie Fink

Lea Ottilie Fink [2018](#) developed a different theoretical framework to explain what motivates companies to join the SBTi. Instead of analysing the motivations from only the companies perspective, she examined the cooperation of voluntarily contributing companies and the climate initiative SBTi. In order to understand the interaction between SBTi and the companies, the behaviour of these distinct entities needs to be taken into account and how this behaviour is perceived by the other actor. She gained insights into this by interviewing companies that have already joined.

Building on Ostrom's collective action attributes categorization, she broke down the structural features of the SBTi-companies cooperation into 7 attributes. These attributes were further subdivided into 4 organisational and 3 cooperative attributes. Each of these attributes was studied both as an attribute of the companies or the SBTi (organization) and also in relation to how they affect their cooperation.

The organizational attributes can be understood as tools that are "provisioned by a voluntary business initiative" to assist and encourage companies to pursue their strategic objectives related to climate. Thus, they are attributes of the SBTi. Each of these attributes (i.e. the availability of information, the ability to communicate, the existence of informal monitoring and sanctioning, and the benefits at smaller scales) were evaluated by Fink after interviewing the involved shareholders and given two scores: the quality of the SBTi attribute and its perceived importance by the companies

Table 2.1: Summary of results for the organizational attributes. +, ~ and – stand for High, Limited, Low respectively. Formal monitoring is not within SBTi vision, hence will be ignored for the rest of the thesis (Taken from Fink, 2018, p. 62)

Organizational Attributes O1-4	Value
O1: Information	
Availability of information on climate change and costs & benefits of participation	(+)
Importance of information on costs & benefits of participation	(~)
O2: Communication	
Opportunity to communicate with participating firms and other stakeholders	(~)
Importance of communication	(~)
O3: Monitoring & sanctioning	
Formal monitoring & sanctioning	(-)
Informal monitoring & sanctioning	(~)
Importance of informal monitoring & sanctioning	(~)
O4: Benefits at smaller scales	
Excludable benefits from participation	(+)
Importance of excludable benefits of SBTi participation	(~)

The analysis of SBTi's organizational attributes yielded the following insights. First, the companies interviewed were satisfied with the quality of information provided by SBTi, however they did not consider it an important factor regarding their decision for voluntarily joining. Second, communicating the SBTs to customers was not considered essential, while they considered communicating them to corporate stakeholders of great importance; this echoed the findings of van Hilten's where end-consumers were found less significant than business clients. Third, SBTi only informally monitors the progress of the targets, which was perceived

by the companies as not very effective since there are no consequences. Fourth, the benefits offered by SBTi, such as mitigation of regulatory uncertainty, were not viewed as particularly significant. (see table 2.1).

The corporate attributes can be understood as the strategic objectives of the companies. The strategic objectives of the companies are driven by their motivations (see Section 2.2.1). As (Fink, 2018) reaffirmed, companies are exposed to regulatory, physical and market risks due to climate change and thus are motivated to mitigate these risks. Thus, Fink's corporate attribute 1, Climate risks, is based on the motivation category of social insurance. Corporate attribute 2, climate reputation is the necessity of companies to keep a moral corporate image. Thus climate reputation is related to the Legitimacy motivation. Thirdly, companies strive for climate leadership which increases their competitiveness and innovation which potentially lead them to be early adopters of SBTi. This is mostly related to the category of Market Success. These attributes were evaluated by interviewing SBTi member companies on their perception of themselves and how SBTi can help them in their strategic objectives (i.e. their perception of the help SBTi can offer to their specific objectives), thus again given two different scores.

Table 2.2: Summary of results for the corporate attributes. +, ~ and – stand for High, Limited, Low respectively. (Taken from Fink, 2018, p. 73)

Corporate Attributes C1-3	Value
C1: Climate risks	
Climate risks	(+)
Potential of SBTi participation to guide against these risks	(-)
C2: Climate reputation	
Importance of reputation as climate-friendly firm	(~)
Potential of SBTi participation to enhance climate reputation	(-)
C3: Climate leadership	
Striving for climate leadership	(+)
Potential of SBTi participation to enhance climate leadership	(+)

There were several key insights obtained by the analysis of the corporate attributes. First, the climate risks are perceived as very important by companies, however, SBTi is not perceived as an important tool for mitigating those risks. This agrees with van Hilten's finding on internal improvement which is partially connected since in both cases there is a reluctance to accept technical guidance from a third party. The difference here is that internal improvement is only concerned about efficiency while Fink's category of climate risks encompasses physical, regulatory and market risks. Second, Fink concluded from her interviews that climate reputation among customers was not important for companies, regardless of sector, and that SBTi is not perceived as an important tool to increase reputation among consumers. Finally, climate leadership was found to be an

important drive for the companies to join and SBTi is perceived as an organization that can provide this leadership position for them. (see table 2.2).

2.2.4 Stakeholder Pressures and climate action

The relationship between stakeholder pressures and climate action has also been examined extensively in the past decades, under several theoretical perspectives and different formulations. In an effort to converge all these studies into some more comprehensive general conclusions, a recent meta-analysis by Wang et al., 2020, collected data from empirical studies starting from 1996.

They categorized all these studies into two main perspectives, the stakeholder-based view and the neo-institutional based view. The stakeholder-based view focuses on the pressure exerted by different stakeholder groups and their contribution to the company's decision-making towards establishing an environmental strategy. On the other hand, the neo-institutional view perceives companies as part of an organizational field that is subject to institutional pressures such as coercive, normative, and mimetic, that can drive similar behaviors across companies.

Wang et al., 2020 combined these two perspectives to draw a more comprehensive understanding on how institutional norms end up influencing the mechanism of stakeholder pressures. These led them into dividing their analysis into three kinds of pressures. The coercive and social pressures that were derived from the neo-institutional based view (see figure 2.4), the internal pressures which represent pressures from stakeholders within the company such as shareholders, management and employees and finally the market pressure that is concerned with pressure coming from the network other companies surrounding a company in question, such as supply chain firms, competitors, buyers etc.

The internal pressure ranked first in their meta-analysis regarding positive effect towards environmental strategies. It arises mainly from shareholders/investors, managers and employees. As Wang et al., 2020 explains, shareholders are in a dominant position to influence environmental strategies if they value a good environmental reputation and efficient production. The recent growth in responsible investing can lead to implementations of more ambitious plans (Wang et al., 2020). This is the pressure that the CDP Science-Based Targets campaigns are trying to enhance (see section 2.1.3). Manager pressure can be effective towards climate action because the top management can allocate more resources there to give an impression to external stakeholders that the company is concerned with environmental strategies. Finally, employees are considered core members in disseminating environmental awareness and influence environmental strategies.

The second most important pressure was found to be the coercive regulatory pressure coming from the government through new legislation forcing companies to move towards environmental strategies. The market pressure was ranked third overall, which emphasises the importance of the network of companies

influencing each other. The social pressure from public and NGOs was found to be much smaller than the first three.

Furthermore, the meta-analysis categorized companies according to industry characteristics: industries that are manufacturing-based and non-manufacturing. The results showed that non-manufacturing industries (such as financial services, transport etc) are more prone to stakeholder pressures to shift towards greener practices. The authors believed that this might be due to the lower costs for the non-manufacturing companies to reduce their emissions, thus easier for them to respond to stakeholder pressures.

2.2.5 Empirical findings on stakeholder pressures on companies to join SBTi

There weren't studies focusing exclusively on the pressures on companies to join SBTi, but there were several findings reported in empirical and statistical reports on SBTi that were connected to specific pressures.

According to Freiberg et al., 2021, a positive correlation was found between the fraction of committed companies and the likelihood for a company of the said sector to commit. This was justified as an indication that market pressure is relevant to SBTi uptake. Another interesting and unexpected correlation was found regarding coercive pressure (Bolton & Kacperczyk, 2022). Companies from countries with intended nationally determined contributions (INDCs) were more likely to commit. In contrast, the companies in countries that later proceeded to move to nationally determined contributions (NDCs) (i.e. making their planned emissions reductions official) were less likely to join. The authors gave the possible explanation that in INDCs companies join SBTi to signal their governments that they intend to accept changes to facilitate climate action. When governments make intentions national, companies take a more passive role since the state has taken the responsibility to reduce the emissions. Furthermore, companies that had internal targets for emissions before, have a higher probability in setting an SBTi target (Freiberg et al., 2021). Lastly, higher carbon intensive sectors and low- and middle-income countries have shown a lower rate of SBTi commitments and targets (Bjørn et al., 2022).

As it has become apparent, pressures and motivations overlap to a great extent. In this thesis, pressures are conceptualised as an external force pushing our agents- companies- towards SBTi commitment and motivations are conceptualised as a driver of the company as a singular entity. The several frameworks described up to now were combined in the next section, together with Erin Meyer's culture map as a step before the model conceptualisation.

2.3 Theoretical Building Blocks

2.3.1 Culture map

As discussed in 2.2.1 on the motivations of companies for climate action, organizational culture has been found to be a relevant factor as a means of stimulating climate action within a company. As mentioned

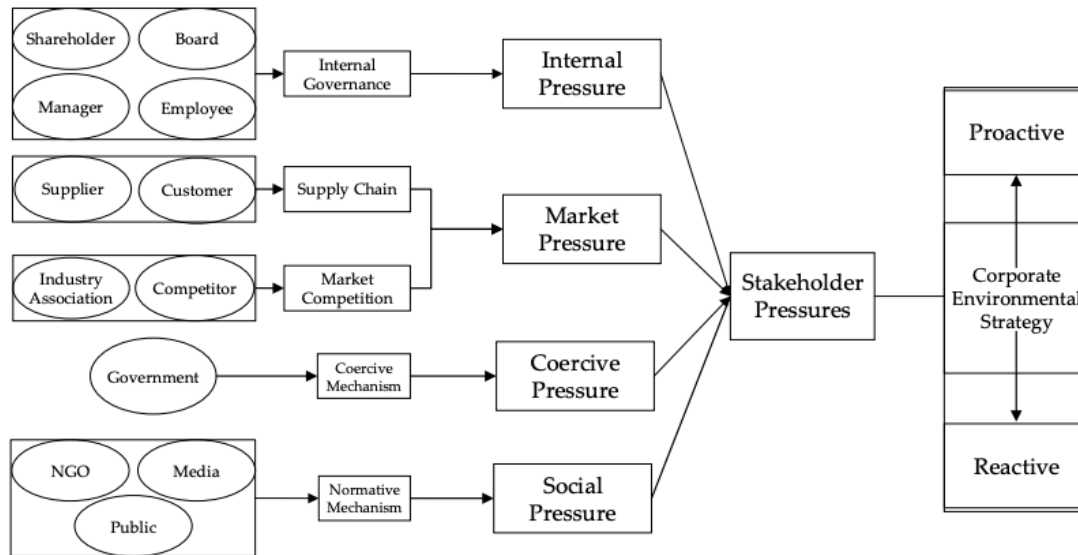


Figure 2.4: The different stakeholder pressures that lead to climate action (Taken from Wang et al., 2020, p. 5).

previously, the Agent-based model will treat companies as agents. Thus agents within the company are beyond our scope and would only be included as part of the internal pressures. In order to include the concept of organizational culture, a culture map framework is used to assign characteristics to companies based on their country of origin.

The Culture Map is a framework developed by Erin Meyer (2014) that identifies and quantifies eight dimensions of culture that are relevant to cross-cultural interactions: communicating, evaluating, leading, deciding, trusting, scheduling, disagreeing, and persuading (details in Table 2.3).

This framework provides insights for organizations to understand how the decision-making process is affected in different countries by culture. By using the Culture Map to better understand cultural differences and preferences, the SBTi can make more informed decisions that take into account the perspectives and needs of diverse stakeholders. This can lead to more effective decision-making and better outcomes for the organization as a whole.

The assumption that organizational culture is affected only by the country of origin is of course not all-encompassing, however for the sake of simplicity in the model, it was decided to keep only this framework as the guiding system. It is also important to note that, SBTi's criterion for multinational companies to join is that all the subsidiary companies join too. Thus, the country of origin of the main company is the only country that plays a role which fits with our assumption.

Table 2.3: Cultural dimensions explained based on (Meyer, 2014)

No.	Dimensions	Scales	Description
1	Communicating	Low ↔ High Context	In low-context cultures, communication tends to be precise, explicit and statements are taken into face-value. In high-context cultures the communication is more layered and contains nuances with messages being more implicit.
2	Evaluating	Direct ↔ Indirect Negative Feedback	This scale measures the preference for direct versus diplomatic negative feedback.
3	Leading	Egalitarian ↔ Hierarchical	In egalitarian cultures the power distance between a director and an employee is low. Thus, there is a tendency of flat organizational structures while communication skips hierarchy. In hierarchichal cultures the power distance is higher thus multilayered and more fixed organizational structures and communication.
4	Deciding	Consensual ↔ Top-down	In consensual cultures, decisions are made through consensus if possible. The decision-making can take longer since all parties involved need to agree. When the decision is finalised, it becomes fixed and inflexible for further changes. Its implementation then moves rapidly. In top-down cultures, decisions are taken by a director, thus they are taken faster. However, this leads to slower implementation since obstacles may surface due to new information from the rest of the parties that was not considered, which might lead the director to revisit and alter the decision.
5	Trusting	Task ↔ Relationship-based	In Task-based cultures, trust and work relationships are based on how work takes place. Relationships can be built and dropped easily. In Relationship-based cultures, trust and relationships between stakeholders are built slowly and need activities outside work.
6	Scheduling	Linear ↔ Flexible Time	In linear-time scheduling cultures, the steps of a project are approached in a fixed sequence, sticking to the deadlines. There is less flexibility and there is emphasis on disciplined organisation. In flexible scheduling cultures, project steps are approached in a less strict manner and interruptions and changes are more acceptable if something arises; adaptability and flexibility are more important than organisation.

7	Disagreeing	Confrontational ↔ Avoids confrontation	In cultures that are more confrontational , disagreement is appropriate and is not perceived as negative for the relationships in a cooperation. In cultures that avoiding disagreement is the norm, disagreements are generally perceived as negative and inappropriate for a work relationship.
8	Persuading	Principles ↔ Applications	In principles-oriented cultures, people generally prefer answering the why of an action than the how. The preference manifests in reports building on theoretical arguments before moving to conclusions. The conceptual principles are important. In application-oriented cultures, people favour the how. Thus, the preference is to start with a fact/conclusion and then back it up with concepts. Reports tend to start with an executive summary and theoretical and philosophical discussions are avoided within business.

2.3.2 Combining the motivation frameworks of Fink and van Hilten and their inclusion to the selected theoretical frameworks

The two frameworks by Fink and van Hilten that were discussed above have their own merits. van Hilten builds upon a series of previous academic papers using the categorization of motivations into 4 groups: market success, internal, improvement, social insurance adding a fifth one, the organizational culture. Her quantitative analysis provides a more concrete appreciation of her results.

Fink's framework acknowledges the duality of the motivations, as an interaction between SBTi and the companies. SBTi can affect some of the drives for companies to join if it improves its performance of its organizational attributes as well as the way companies perceive the benefits they could get if they join.

In our model conceptualisation, these two frameworks are fused together, as shown in table 2.4. The corporate sustainability management motivations are matched with the corporate attributes of climate reputation, climate leadership and climate risks. This is done so that we can follow Fink's framework and include performance improvements of SBTi while aligning as much as possible with the framework that van Hilten developed. The organisational attributes of information, communication, monitoring and benefits will be used in the parametrisation of SBTi.

Furthermore, the organizational culture category will be modelled using the culture map by Meyer. The only category that is not explicitly included is internal improvement. As mentioned above, van Hilten found little evidence of it being relevant for companies to join SBTi. Furthermore, the increased efficiency is overlapping with market success, since any process optimization could be in order for a company to increase its success.

Table 2.4: The Table below draws the connection between the motivations explained in section 2.2.1 and the frameworks that will be used.

Motivations for Corporate Sustainability Management (van Hilten, 2022, p. 22)	Translation to the frameworks used for the study of SBTi
Legitimacy- A corporate's ambition to have actions that are accepted and appropriate within a social system consisting of norms, values, beliefs, and definitions.	Climate reputation- Companies "perceive a positive reputation related to climate activities as important for their overall corporate image." (Fink, 2018, p.37)
Market Success- A corporate's willingness to increase corporate turnover, competitiveness, brand equity or innovation as a consequence of consumer, investors, and competitors behaviour in the field.	Climate Leadership- Companies strive for leadership which "implies that firms are exceeding existing societal expectations and hence standing out among their peers, being especially visible to knowledgeable stakeholders, such as suppliers, rating agencies and academic research, as well as competing firms". (Fink, 2018, p. 39)
Internal improvement- A corporate's aim for process and resource use improvements that lead to increased efficiency in the form of reducing costs and resources.	<i>This motivation is not explicitly included. Following, van Hilten findings which showed no relevance of this motivation specifically for SBTi it was decided to skip this motivation.</i>
Social Insurance- A corporate's goal to gain insurance by mitigating risks to protect the corporate from potential reputation losses, or shareholders from financial distress.	Climate risks- Firms are "exposed to physical, regulatory or market risks resulting from climate change" and strive to mitigate them. (Fink, 2018, p. 35)
Organizational Culture- A corporate's cultural change and transformation as a means of stimulating corporate climate action from within the firm.	Culture map- decision-making process is affected in different countries by culture. The assumption is that sustainable management is also affected by culture. (Meyer, 2014)

2.3.3 Stakeholder pressures simulated in the model

The pressures that are simulated in the model are taken from the framework described above (Wang et al., 2020). The coercive and social pressures are excluded since regulations and the public are out of the scope of the model. The two categories of pressures simulated then are internal and market pressures. The conceptualisation of those in the model will be explained in the next chapter. The correlation coefficients found in the meta-analysis of Wang et al. are used as weights in the modelling.

Table 2.5: The Table below presents the correlation coefficients found for the stakeholder pressures relevant to our model. Taken from Wang et al., 2020

Stakeholder Category	Pressure Coefficient
Shareholders	0.253
Managers	0.254
Employees	0.238
Market Pressure	0.210
Industry Characteristics	Pressure Coefficient
Manufacturing	0.232
Non-manufacturing	0.358

Chapter 3

Model Conceptualisation and Formalisation

This chapter is concerned with the conceptualisation and formalisation of the model and the sources of data that were used, aligning with the research methodology (Section 1.2.4) and data sources described in the Introduction. The chapter is divided into two main sections: the 'Conceptual Framework' and the 'Formal Model.'

In the Conceptual Framework (Section 3.1.1), the structure and components that constitute the model is explored, starting with a brief overview in Section 3.1.1. We then move into the characterization of our agents, the CDP high-impact companies in Section 3.1.2, followed by a description of the environment in which they operate (Section 3.1.3). The types of interactions that occur between these agents and between the agents and the environment are also discussed (Section 3.1.4). Finally, the concept of scheduling i.e. which process takes place first and how the progression is conceptualised is described in Section 3.1.5. The task of the conceptualisation is to answer the question "What it is that we are modelling?".

In the Formal Model (Section 3.2), the precise mathematical and algorithmic formulations that make the conceptual model operational are explained. Parameters and variables are defined in detail in Section 3.2.1, establishing the building blocks for subsequent computations. The Network Structure is then explained and formulated in mathematical terms in Section 3.2.2. The last three subsections of the Formal Model, detail the three main process that shift agent's state from aware to committed and finally to setting a target. The task of formalisation is to answer the question "How to model the conceptualised system?".

3.1 Conceptual Framework

3.1.1 Overview

The model intends to simulate the process of CDP high-impact companies (Section 2.1.3) becoming aware of the SBTi, considering joining, committing and ultimately setting a target for the period May 2015, when

SBTi was first launched (SBTi, 2015) until May 2025. The companies can move through four different states (see figure 3.1).

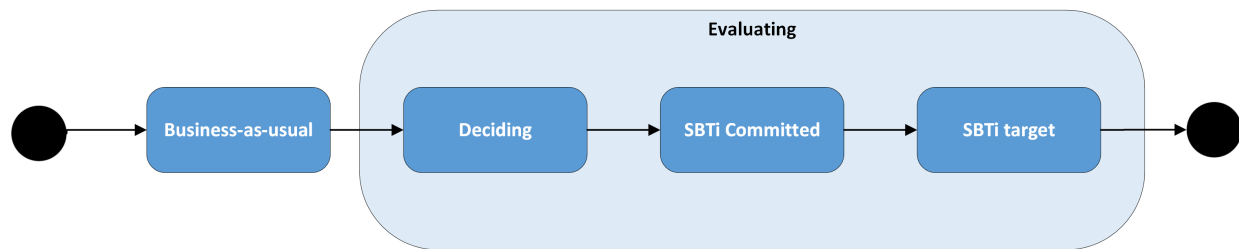


Figure 3.1: State diagram of a company.

The first step towards setting a target is awareness. Each company has the potential of joining the SBTi as long as its board is aware of its existence. The company can become aware of SBTi either through the SBTi CHIS campaign or through the network of the companies that it is associated with (suppliers, buyers, competitors etc). This first step has no empirical data but it was deemed necessary, in order to comprehend the change of reach SBTi with time, which could also vary in different countries or sectors.

The decision to commit to SBTi depends on two main factors: the stakeholder pressures (internal pressures and market pressures), and its corporate motivations towards achieving leadership, reputation and mitigating climate risks. The performance of SBTi in its organisational attributes (Section 2.2.3) influences this step too. Each organizational attribute and pressure in the model is influenced by a chosen culture feature of the country of origin of the country as discussed in Section 2.3.1. The decision on which culture dimension fits with which pressure and/or motivation was made by approximation by the author.

The market pressure dimension depends again on the network of companies that are associated with the company in question. The company is assumed to be influenced by its suppliers, buyers and competitors as discussed in the Theoretical Underpinning chapter. Commitment drivers are presented in figure 3.2.

The companies that are aware of the existence of the SBTi consider committing in every board meeting. The companies that end up committing start working towards setting a target. The scheduling culture (see culture map) influences the uncertainty of working towards the target setting completion while the deciding culture affects the speed of completion (more in the processes section). Companies could have internal emissions reduction targets which could speed up the process between committing and setting a target.

3.1.2 Agents

The model's central entities and only agents are the companies that were included in the aforementioned CDP climate high-impact sample (CHIS) that was curated by CDP in 2019 (see section 2.1.3). Thus, 2233 companies are created representing the initial sample of high-impact companies, assuming those companies

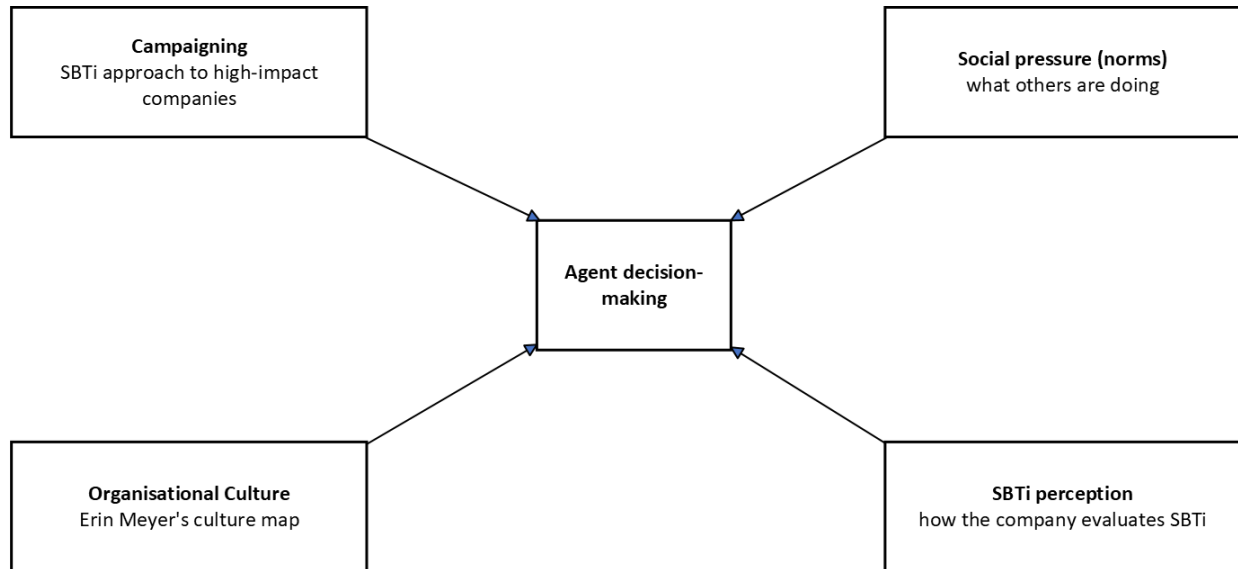


Figure 3.2: Drivers of Agent Behaviour.

existed and were high-impact before the campaigns started in 2020. Each company begins with some specific characteristics (initial parameters).

First, there are some country-based parameters which influence the company's behaviour, mainly due to the cultural values associated with the country of origin. Each company is randomly assigned to a country from the list of possible countries taken from SBTi, 2022 (p. 23,24), reflecting the distribution in the SBTi progress report. The cultural dimensions for each country were downloaded from Meyer, n.d., and companies were assigned values based on a default normal distribution of a factor equal to half of the mean value to add a moderate fluctuation.

Second, the companies are assigned to sectors based on the percentages of companies recorded in the SBTi progress report (p. 25). The sector influences the agent's emission level. The percentages of emissions per sector are taken from Oliver Wyman, 2021. The total emissions of the CDP SBTi high-impact campaigns were estimated to be 13.5 GT GHG emissions Oliver Wyman, 2021, hence the percentages of the emissions are used to divide emissions per sector for our company sample. The emissions are then distributed randomly around the mean value for one company per sector. The lack of data for the specific sectors used by SBTi has led to several assumptions being made in order to provide a realistic view. These assumptions are discussed in the Appendix, Section A.2. Furthermore, sectors are divided into two groups: manufacturing and non-manufacturing. The decision of this split is also discussed in the Appendix, Section A.2. The sector type, as elaborated in the theoretical underpinning, influences the market pressure that a company would feel.

Third, each company is randomly assigned an internal target value (0 to 1). This parameter was deemed necessary since it has been observed that companies with established environmental strategies could accelerate submissions (Freiberg et al., 2021). Even though no data was found regarding the time between commitment

and setting a target, estimations were made using the available data (Appendix Section A.4). The estimated average time between the two states is 0.53 years or ~ 6.4 months. This is much lower than the SBTi deadline of two years.

Finally, companies are randomly assigned a value for each of the three corporate motivations discussed in Section 2.3.2: climate leadership, climate reputation and climate risks awareness.

The company has state variables starting from unaware, moving to aware, committed and setting a target. If a company does not manage to set a target after two years of being committed it loses its committed status. It also has motivation and pressure variables that are calculated depending on several variables such as "connections" with other companies, campaigns and culture dimensions which are discussed in the environment interactions sections.

3.1.3 Environment

The environment in which the companies operate is a network where nodes represent companies and edges represent connections between them. The initial network structure is generated using a connection matrix which provides probabilities for the companies to be connected with other companies based on geographical and sector similarities as well as communication similarities based on culture. The connection matrix allows companies to join even if they don't have these similarities to some extent, allowing for factors such as global economic interests and similar regulations conditions that are not explicitly modelled are also taken into consideration. The formalisation of this will be revisited in later sections.

The network is dynamic allowing companies to change and increase their number of connections with time based on the connection matrix. This could be considered a variation of the Barabasi-Albert model (Bertotti & Modanese, 2019). The network allows preferential attachment and could lead companies to become very influential regarding awareness and commitment due to their large amount of connections. The rewiring could allow the network to grow over time.

The connections that a company has can influence it by making it aware of the SBTi. Furthermore, market pressure which is pressure coming from a company's competitor, buyer and supply companies could increase or decrease according to the change in its connections. The idea is to allow the model to explore emergent patterns arising from the interaction and exchange of information between individual nodes.

3.1.4 Interactions

The ABM model represents two types of interactions: between companies which is based on the network and between the agents and the SBTi campaigns and strategies.

There are three main processes in the model: moving from unaware to aware, aware to committed and committed to setting a target. The awareness process is a combination of interactions between companies

and between the company and the SBTi. The SBTi through constant campaigning makes companies become aware of its existence. Awareness also spreads through the network connections; a company can learn about SBTi from one of its 'neighbours'.

The commitment process is influenced also by both but it is largely an internal process. The company's decision to commit is influenced by its motivations (climate risks, climate leadership and climate reputation) each of which is influenced by one culture dimension as well as by its internal pressures (shareholder, employee, and manager), which depend on its country of origin, culture, and sector. The SBTi interacts with this process through campaigns affecting these aspects. For example, the existing CDP-SBTi campaign increases shareholder pressure. The network of companies affects this process by increasing the market pressure when more companies become committed.

Finally, the progress towards submission process is mainly an internal process but it is also affected by the SBTi. The company works towards the target and its progress depends on its internal target and the cultural dimensions of scheduling and deciding (more on these choices in section 3.2). The SBTi monitors if the company is within the two-year window and could remove its commitment status.

3.1.5 Scheduling

In this section, a brief description of the order of processes taking place per time step is given. The step of the model is one month, however, the commitment decision takes place only during board meetings. There was no information for the frequency of board meetings for all countries or sectors. The board meeting frequency that is used in the model is taken to be the average board meeting frequency of the 17 countries for which this metric was measured by the global consulting firm Spencer Stuart (Spencer Stuart, [2022](#)).

The sequence of events per step starts with collecting the relevant data of the current configuration of the model. The data collected will be discussed at a later point. The model then allows the companies to update their state based on the interactions with the environment and the rest of the companies. The companies follow a linear progression: if not aware, they could turn aware based on the fraction of aware neighbours they have; if aware but not committed and there is a board meeting at the specific step, motivation and pressure are calculated to check if the company would be willing to commit at that step; if aware and committed the company works towards setting a target.

The third event taking place is the effect of campaigns run by SBTi. In the base scenario, the only campaign taking place is the CDP shareholder campaign which increases the market pressure starting from 2020 (from the 60th month/step onward). The other potential campaigns will be discussed in Chapter 5: Experiments and Results.

The fourth event is an update of the network connections. The network is updated based on a random rewiring of each company with a potential new connection. This rewiring happens at regular intervals that can be adjusted (value used will be decided during parameter tuning).

The final event is an update of awareness due to networking campaigns and workshops by the SBTi. It is important to note that this is different from the awareness update taking place due to interaction between companies.

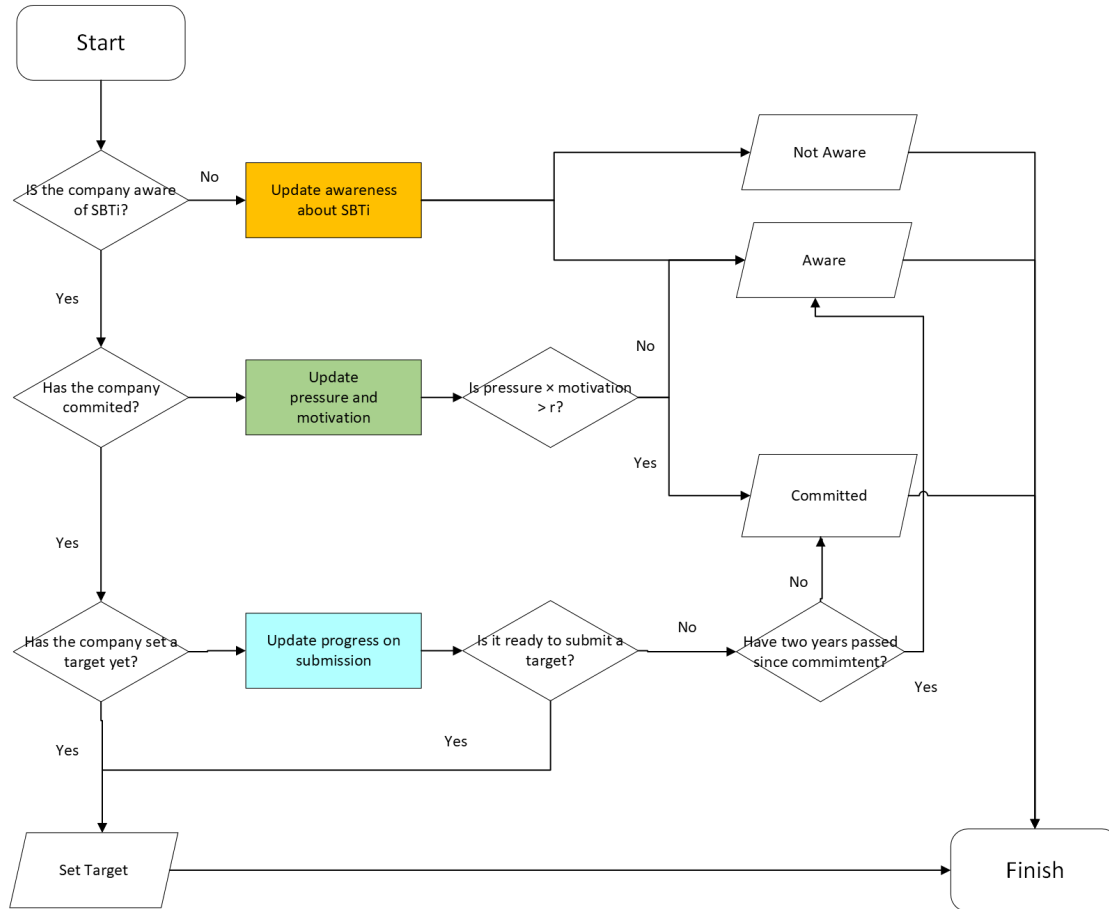


Figure 3.3: Flow diagram of the decision-making process of each company.

3.2 Formal Model

3.2.1 Parameters and Variables

In this section, the parameters and variables that are needed to develop the conceptualised version of the model are listed alongside the type, range and description. Additionally, their sources are indicated where available.

The section is broken down into the parameters of an individual company (Table 3.1), the parameters of the general model (Table 3.2), the variables of an individual company (Table 3.3), and the variables of the model (Table 3.4).

Parameters

Table 3.1: Agent Parameters . Purple: global parameters; Yellow: parameters used in the awareness process; Red: parameters used in the commitment process; Green: parameters used in the target-setting process

Parameter	Type	Range/Values	Description
country	string	e.g 'US'	Country where the company operates, taken from SBTi progress report 2022.
communicating	float	[0, 1]	Communicating value based on country taken from Culture mapping tool (Meyer, n.d.). The range of the values was changed from 0 to 100 to 0 to 1. The values are assigned using a normal distribution with the mean being the original value from the culture map
evaluating	float	[0, 1]	Evaluating value based on country taken from Culture mapping tool (Meyer, n.d.). Same as communicating.
leading	float	[0, 1]	Leading value based on country taken from Culture mapping tool (Meyer, n.d.). Same as communicating
deciding	float	[0, 1]	Deciding value based on country taken from Culture mapping tool (Meyer, n.d.). Same as communicating

trusting	float	[0, 1]	Trusting value based on country taken from Culture mapping tool (Meyer, n.d.). Same as communicating.
disagreeing	float	[0, 1]	Disagreeing value based on country taken from Culture mapping tool (Meyer, n.d.). Same as communicating.
scheduling	float	[0, 1]	Scheduling value based on country taken from Culture mapping tool (Meyer, n.d.). Same as communicating.
sector	string	e.g. 'Chemicals'	Sector where the company operates, taken from SBTi progress report 2022 (SBTi, 2022).
emissions	float	normal distribution around the mean value	Emissions produced by the company. The mean value is calculated using the diagram in CDP Europe Progress report p. 10 (Oliver Wyman, 2021). More details on the data used in the Appendix, section A.2.
sigma	float	e.g. 0.1	Standard deviation used in the normal distributions for cultural dimensions
aware_update_step	integer	1	The frequency at which the awareness process through interaction with neighbour take place. The default is 1 i.e. at every step.
sector_type	string	'manufacturing' or 'non-manufacturing'	The type of the sector was based on the emission intensity. More details in the Appendix, section A.2.
leadership	float	[0, 1]	A randomly generated value representing the intrinsic character of the company regarding climate leadership.

riskawareness	float	[0, 1]	A randomly generated value representing the intrinsic character of the company regarding its consideration of climate risks.
reputation	float	[0, 1]	A randomly generated value representing the intrinsic character of the company regarding climate reputation.
meetings_per_year	integer	10	The board meetings per year during which committing to the SBTi is discussed. The default value is 10 and was calculated using the mean value from the countries for which we have data (Spencer Stuart, 2022) (see Supplementary Materials, excel file StructureData.xlsx, worksheet 'Board Meetings').
internal_target	float	[0, 1]	Pre-existing internal target set by the company. The larger the value, the closer the company is to setting a target after it commits.
work_rate	float	e.g. 0.16	The rate at which companies work towards setting a target. This value will be decided during the parameter tuning (see section 4.4).

Table 3.2: Model Parameters . Purple: global parameters; Blue: parameters used to create the network; Yellow: parameters used in the awareness process; Red: parameters used in the commitment process; Green: parameters used in the target setting process

Parameter	Type	Process Section	Description
num_companies	integer	2233	The total number of high-impact companies (CDP, n.d.).

max_steps	integer	60 and 108 (default)	The total number of steps that the model will run. The start of the model is May 2015 and until the start of the CDP campaigns in 2020 i.e. 5 years (60 months). The model in the end will project the evolution of the model until 2025, which means that the maximum steps will be 108.
alpha	float	0.1 (default)	Weight for companies having identical sectors in the connectivity matrix.
beta	float	0.1 (default)	Weight for companies having identical countries in the connectivity matrix.
gamma	float	0.1 (default)	Weight for communicating culture dimension similarity in the connectivity matrix.
delta	float	0.02 (default)	Base connectivity probability in the connectivity matrix.
M	ndarray	$(num_companies \times num_companies)$	The connection matrix contains the probability of each combination of companies to end up having a connection.
rewiring_frequency	integer	1 (default)	How often the network is rewired.
companies_turn_aware_per_round	integer	1 (default)	The number of companies turning aware due to SBTi actions every time the awareness is updated.
steps_per_round	integer	1 (default)	How often the awareness due to SBTi actions is updated.
information	float	[0, 1]	Information is one of Fink's organizational attributes which rates SBTi effectiveness in providing information and its importance for the companies. It is a randomly generated value.

communication	float	[0, 1]	Communication is one of Fink's organizational attributes which measures SBTi effectiveness in facilitating communication and its importance for the companies. It is a randomly generated value.
monitoring	float	[0, 1]	Monitoring is one of Fink's organizational attributes which rates SBTi effectiveness in monitoring its members and its importance for the companies. It is a randomly generated value.
benefits	float	[0, 1]	The 'excludable benefits' is one of Fink's organizational attributes which rates SBTi offered benefits and its importance for the companies. It is a randomly generated value.
sbti_attributes	float	[0, 4]	Aggregate attribute calculated as the sum of information, communication, monitoring, and benefits.
shareholder_pressure_coefficient	float	0.253	Taken from Wang et al., 2020 and used as a weight in equation 3.3.
manager_pressure_coefficient	float	0.254	Taken from Wang et al., 2020 and used as a weight in equation 3.4.
employee_pressure_coefficient	float	0.238	Taken from Wang et al., 2020 and used as a weight in equation 3.7.
manufacturing_pressure_coefficient	float	0.232	Taken from Wang et al., 2020 and used as a weight in equation 3.8.
non_manufacturing_pressure_coefficient	float	0.358	Taken from Wang et al., 2020 and used as a weight in equation 3.8.
market_pressure_coefficient	float	0.210	Taken from Wang et al., 2020 and used as a weight in equation 3.5.

motivation_threshold	float	5 (default)	The threshold is used as a multiplier to the randomly generated number and affects the amount of companies that can become committed.
pressure_threshold	float	5 (default)	The threshold is used as a multiplier to the randomly generated number and affects the amount of companies that can become committed.
internal_target_range	list	[0,1] (default)	The range of possible values for an existing internal target for the companies of the model.
max_comm_duration	float	24 (default)	The deadline for a company to set a target is 24 months. After 24 months, if the company has not set a target they lose their committed status.

Variables

Table 3.3: Agent Variables . Blue: variables calculated during the network process; Yellow: variables calculated during the awareness process; Red: variables calculated during the commitment process; Green: variables calculated during the target-setting process.

Variable	Type	Process Section	Description
neighbors	list	Network Configuration (Section 3.2.2)	The other companies that the current company is connected to in the network.
num_connections	integer	Network Configuration (Section 3.2.2)	The number of connections.
is_aware	boolean	Awareness process (Section 3.2.3)	Indicates whether a company is aware of the SBTi
pressure	float	Commitment Process (Section 3.2.4)	A quantitative value of the stakeholder pressures that influence the company to commit at the specific step.

motivation	float	Commitment (Section 3.2.4)	Process	A quantitative value of the corporate motivations that influence the company to commit at the specific step.
commit_step	integer	Results		Saves the step of commitment
is_committed	boolean	Commitment (Section 3.2.4)	process	Indicates whether a company is committed to the SBTi.
target_progress	float	Setting a target (Section 3.2.5)		The progress towards successfully submitting a target. When surpassing 1 the target is set
commitment_duration	integer	Setting a target (Section 3.2.5)		The number of months that has passed since company committed without reaching the submission of a target. If it reaches 24 months, the company loses its status as committed
failed_to_set_target	integer	Results		Indicates whether a company has failed to set a target before the deadline.
target_set_step	integer	Results		Saves the step that the target was set
has_target	boolean	Setting a target (Section 3.2.5)		Indicates whether a company has set an SBTi target.

Table 3.4: Model Variables . Blue: variables calculated during the network process; Yellow: variables calculated during the awareness process; Red: variables calculated during the commitment process; Green: variables calculated during the target-setting process

Variable	Type	Process Section	Description
step_counter	integer	All processes	Counts the steps from the start of the model run.
G (network)	NetworkX Graph	Network configuration (section 3.2.2)	The network that represents companies (nodes) and their connections (edges).

3.2.2 Network Structure

As mentioned in the Environment section, the network that is created is made of nodes that represent companies. The initial structure of this network is based on a connectivity matrix M that contains the probabilities for every possible pair of companies to end up connected.

The probability for two companies to establish a connection relies on four features:

1. **Sectoral similarity:** When companies operate within the same sector, the likelihood of being competitors and influencing each other's strategic decisions increases. Therefore, the probability of connection is higher. This factor is weighted by the parameter α .
2. **Geographical similarity:** Companies that have their headquarters in the same country are more likely to be connected as suppliers, buyers, or through industrial associations. The weight of this country-based similarity is denoted by β .
3. **Communicating dimension:** Erin Meyer rates cultures based on how they communicate, from low context (precise, explicit) to high context (layered with nuances) (Meyer, 2014, p. 31). This dimension can create a barrier when it comes to connections between companies. The communicating similarity is calculated using a Gaussian function. The communicating importance is close to higher when the values of communicating dimension are close and decreases as the difference increases. The weight of this feature is denoted by the parameter γ .
4. The connection matrix allows for a small probability that companies could be connected due to factors not explicitly considered in the model. This is denoted by δ .

This results in the following equation:

$$M[i, j] = \alpha * I(s_j = s_i) + \beta * I(c_j = c_i) + \gamma * e^{-0.2*d^2} + \delta \quad (3.1)$$

where $M[i, j]$ is the connection probability between company i and j , s_j and s_i are the sectors of companies i and j , c_j and c_i are the countries of companies i and j , $I(x)$ is an indicator function (it is 1 when x is true and 0 otherwise) and d is the difference between the communicating dimension of company i and company j .

This connection matrix is used to initialize the model's network (G). As discussed before, the dynamic aspect of changing connections is modelled by rewiring the model every set of steps. The idea is to provide a dynamic environment in which companies come in contact with different companies during the modelled time period.

During each rewiring step (using `rewiring_frequency` parameter), each company i randomly selects a company j that is not yet connected. The probability of company i establishing a connection with the selected company j is based on $M[i, j]$. A random number between 0 and 1 is generated and if it is less than $M[i, j]$,

a connection is established. The connection probability can be expressed as:

$$P_{connect}(i, j) = M[i, j] \quad (3.2)$$

If a new connection is made, another company is randomly selected from among the connected ones to assess whether a disconnection will occur. The probability of company i disconnecting from the selected connected company j is again calculated by $1 - M[i, j]$. This is to indicate that stronger attachment (higher $M[i, j]$) results in a reduced likelihood of disconnection.

3.2.3 Awareness Process

As discussed in the conceptualisation, the awareness process is influenced by two factors: first by the SBTi's constant campaigning, outreach and workshops which make companies aware of its existence; and second by the 'neighbours' of a company that are already aware.

The first aspect is an environment-agent interaction. The interaction is modelled is by having the model periodically turn a set number of companies aware (controlled by the variables `steps_per_round` and `companies_turn_aware_per_round` from table 3.2). This approach also ensures that even in a network without aware companies, companies will still have the opportunity to become aware.

The second, aspect is an agent-agent interaction. The probability of a company becoming aware is assumed to be equal to the fraction of neighbours that are aware at a specific step (`aware_update_step`). This simulates the influence they have on each other.

3.2.4 Commitment Process

The commitment process only starts when a company becomes aware and its two main drivers are the stakeholder pressures and company's motivations.

The **stakeholder pressures** that are modelled are the internal pressures (employee, shareholder and manager) and the market pressure. The **employee pressure** represents the pressure that could arise to join SBTi from the employees. The assumption made here is that this pressure is influenced by the **leading** dimension of the culture map which distinguishes between more egalitarian or hierarchical cultures (more in section 2.3.1. This is because it is expected that in more egalitarian cultures, there's increased involvement and dialogue between managers and staff, making employee opinions more influential. The **manager pressure** to join the SBTi can also arise due to the people in charge of the operational activities of a company (i.e. the managers) wanting to be in line with the 1.5°C. The culture dimension that was deemed more suitable here was the **scheduling** dimension. This dimension describes how strict a specific culture is to deadlines and procedures. It is assumed that in linear-time cultures managers will apply more pressure to align the companies to the SBT targets. The **shareholder pressure**, which is also the focus of the SBTi

CDP high-impact companies campaigns, represent the pressure that is applied by company shareholders to shift towards greener practices which could lead towards joining SBTi. This pressure is assumed to be influenced by the **disagreeing** dimension which describes if a culture is more avoidant in disagreeing or more confrontational. A more avoidant to confrontation group of shareholders would not strive to change the status quo (i.e. keeping the business as usual) while a higher confrontation could lead to more pressure. Finally, the **market pressure** is pressure coming from peers (competitors, buyers, suppliers). This could be connected to the **trusting** dimension of a culture since a more relationship-based culture could mean more influence by trusted companies' decisions. The market pressure, since it is not internal, it is affected by the network of the companies. The higher the ratio of companies connected to a company committed to the SBTi the higher the pressure.

These pressures are also influenced by the type of the sector. As Wang et al., 2020 concluded, non-manufacturing companies are more influenced by pressures than manufacturing companies.

The calculation of a company's internal pressure can be summarised in the equations below:

$$shareholder_pressure = (1 - disagreeing) * 0.253 \quad (3.3)$$

$$manager_pressure = (1 - scheduling) * 0.254 \quad (3.4)$$

$$employee_pressure = (1 - leading) * 0.238 \quad (3.5)$$

$$internal_pressure = \frac{shareholder_pressure + manager_pressure + employee_pressure}{3} \quad (3.6)$$

The internal pressure is taken to be the mean of the 3 pressures. Note that the culture dimensions are subtracted from 1. The culture values are from 0 to 1. In those cases, higher value for disagreeing means more avoidant, for scheduling more flexible and for leading more hierarchical. Since we want the opposite to have a higher effect, the values were reversed so higher weight would be for countries that are confrontational, linear-time and egalitarian. The values 0.253, 0.254 and 0.238 are taken from the correlation coefficients in Table 2.5.

The calculation for the market pressure is summarised in the equation:

$$market_pressure = 0.210 * trusting * \frac{committed_neighbours}{neighbours} \quad (3.7)$$

As mentioned before, market pressure depends on how many companies that are connected to the company in question have committed. If the company has no connections, market pressure is defined as zero.

The total stakeholder pressure then is defined as:

$$\text{pressure} = (\text{market_pressure} + \text{internal_pressure}) * \text{sector_factor} \quad (3.8)$$

The `sector_factor` is either 0.232 (if `sector_type= 'Manufacturing'`) or 0.358 (if `sector_type= 'Non-Manufacturing'`) to weigh in the importance of the sector.

The **motivation** is affected by two parts the corporate attributes and the organizational (SBTi) attributes, as discussed in section 2.2.3 and individual corporate attributes.

The organizational attributes are model attributes that influence equally all the companies. The organizational attributes value affecting the overall motivation variable is calculated by aggregating the different attributes:

$$\text{sbt_attributes} = \text{information} + \text{communication} + \text{monitoring} + \text{benefits} \quad (3.9)$$

The corporate attributes are climate leadership, climate risks (awareness) and climate reputation. The **climate leadership** is the strive of companies to stand out as leading entities in climate action. It is assumed to be influenced by the **leading** culture dimension. The reason is that cultures that are more egalitarian in their approach to leadership may be more likely to encourage innovation and social responsibility. The **climate risks** attribute describes the strive of companies to mitigate the market, regulatory and physical risks they are into. This attribute was connected to the **disagreeing** dimension since cultures that are more willing to confront would have companies that are more willing to acknowledge and address climate-related risks and challenges, which can help identify potential risks and develop effective mitigation strategies. Finally, **climate reputation** discusses the importance that companies show to have legitimacy and be accepted by peers regarding their climate actions. This attribute was connected to **trusting** dimension, since cultures that are more task-based in their approach to trust may be more focused on demonstrating results and competence which can help to build credibility around the company's climate-related actions.

The corporate motivation is then calculated as follows:

$$\text{motivation} = (\text{riskawareness} * \text{disagreeing}) + (\text{reputation} * \text{trusting}) + (\text{leadership} * \text{leading}) \quad (3.10)$$

This is then summed up with the `sbt_attributes`. The motivation and pressure are assumed to act together influencing the company to commit. The product of the two values shows how more or less possible

it is for a company to join. This approach tries to integrate the pressures of the different stakeholders (external) with the internal character of the decision-making of the company.

The commitment process is only evaluated during board meetings (meetings_per_year = 10). The value is then compared with a random generated number and if it is greater than the number the company becomes committed.

3.2.5 Target Setting Process

Once the company is committed, it starts working towards setting a target. It has 24 months (commitment_duration from table 3.3) to complete this task and if it doesn't, it loses its status as committed. There is a global value for the rate of progress per step (work_rate from table 3.2) which is then influenced (multiplied) by the deciding dimension of each company. The deciding dimension is chosen here because in consensual cultures, there is an emphasis to make decisions with consensus. This decision-making process tends to take longer since all parties involved need to agree. The slow-decision making leads to less conflicts during the implementation however we are modelling just the decision-making process i.e. up to the setting of a target. Thus, consensual cultures lead to slower progress per step.

The possibility of a company working towards setting a target at a specific step is monitored by the scheduling dimension value. The reasoning is that in flexible scheduling companies, the project progression deadlines and steps are approached in a less strict manner and interruptions and changes are more acceptable. Thus, companies might not work towards the target at a specific step due to their scheduling dimension being lower than a randomly generated number.

The equation that describes this process is the following:

$$\text{target_progress}(t) = \text{target_progress}(t - 1) + (\text{deciding} * \text{work_rate}) \quad (3.11)$$

where t represents the current time step. The company sets a target when the target_progress surpasses 1.

Chapter 4

Verification, Sensitivity analysis and Parameter Setup

This chapter serves as a comprehensive guide through the various steps taken to validate the model's functionality and reliability after it has been implemented.

The model was implemented using Python 3.9.16 and the open source Mesa 1.2.1 library which is a library built to provide the basic components needed to implement an agent-based model, including model and agent classes, a scheduler for sequence determination, and a data collection tool.

Following implementation, the model underwent a multi-level verification process (Section 4.1). Three distinct phases of verification tests ensured the model's soundness: single-agent, interaction, and multi-agent testing.

The multi-agent testing phase was partly done using open exploration (Section 4.3.1) of the model and agent parameters and sensitivity analysis which tested how "sensitive" outcomes are to changes in input parameters 4.3.2. However, the sensitivity analysis serves the extra purpose of identifying the most significant parameters. Due to computational constraints, a full parameter tuning for all variables was not feasible. Therefore, sensitivity analysis was specifically used to identify the most significant parameters. For the remaining parameters, values were assigned based on educated guesses, falling within the ranges established through open exploration.

The most significant parameters were then allowed to vary in the parameter setup (Section 4.4) to identify combinations that match reality. Analytic tools from the Exploratory Modeling and Analysis (EMA) 2.4.0 workbench python package and Sensitivity Analysis Library for Python (SALib) were used for the open exploration and sensitivity analysis and the parameter setup. The complete code for the model and its analysis is available in the thesis' supplementary material.

This modelling step resulted in a robust and well-understood model with a set of fine-tuned parameters that simulate the progression of CHIS companies that become committed and set a target for the period 2015 until 2020.

4.1 Verification

The task of the verification step of a model is to check if the model does what we wanted it to do. During this step the model is checked against its conceptualisation to ensure that the entities and interactions are correctly implemented in the agent-based model (Nikolic & Ghorbani, 2011). Ghorbani and Nikolic 2011 have divided the task of verification into two levels.

On a higher level, it is important to verify that the knowledge used from existing sources is formalised correctly within the model. The model is trying to present the social reality of what drives companies to join the SBTi. It is based on social facts such as motivation and pressure which are difficult to verify.

Within the simulation and coding, verification's goal is to ensure that the code reflects the existing knowledge. Any outcome should be put into question. Is it something to learn from or does it come from an error in the code? This is broken into three phases: single-agent testing, interaction testing, limited to minimal model and multi-agent testing.

The single-agent testing follows the behaviour of a single agent by running sanity checks using normal inputs and extreme values on the edge of the parameter space to see if the response is logical. Lastly, the agent was tested for extreme number of time-step. The interaction testing is done using a small number of agents to examine if the interactions formalized take place correctly. These two phases were constantly used during the implementation and are used iteratively during debugging.

The third phase, the multi-agent testing checks the variability of parameters used to study any emergent behaviours by the agents. This was done through open exploration of the parameter space and global sensitivity analysis using the SOBOL method (see Sections 4.3.1 and 4.3.2).

The verification performed has led to a model that can be judged bug-free.

4.2 Validation

There are three main ways of validating an ABM model: historic replays of the development of the system in question, scenario testing with the consultation of an expert and modelling method validation (Nikolic & Ghorbani, 2011). In short, historic replays try to recreate the progression from a known starting point over time to compare with with observed values at present. The scenario testing includes a discourse with stakeholders and experts to explore different scenarios that are of interest. Finally, the modelling method validation is based on the notion that several different models can be created in simulating a specific system.

The different models can be compared and validation has to do with the question on if a model provides extra knowledge regarding the system.

In our project, validation only takes place in the form of a historic replay after the parameter setup and is discussed in section 5.1.

4.3 Open Exploration and Sensitivity Analysis

As mentioned in the Verification section, the multi-agent testing is used to better understand the mechanisms that drive the model and the different interdependencies between independent variables and dependent variables. This section is broken down into two steps. The first step is an open exploration of the model, which is a methodology where one aims to explore the output behavior of a model under a wide variety of input conditions or scenarios. The second step is a Global Sensitivity Analysis (GSA) which aims to determine how different input variables impact the outputs in question.

The EMA workbench does a systematic sampling across the uncertainty or decision space ¹. Our analysis focuses on epistemic uncertainties—uncertainties stemming from a lack of knowledge—prior to implementing campaigns (which belong to the decision space and are considered policies in EMA workbench). The uncertainties that are modeled are listed in Table 4.1. These uncertainties are model parameters used to create the model that are not taken from literature (e.g. the culture dimensions values are not used in the sensitivity analysis). The model is run for 60 steps, corresponding to the years 2015 to 2020. This is because high-impact company campaigns are initiated for the first time in 2020-2021. We based our evaluation on 1000 scenarios, each representing a different combination of the uncertainties listed below. It was only run with 1000 companies because the complexity of the algorithm is influenced from the N^2 number of interactions in the network structure, making a run with 2233 companies very computationally intensive.

Table 4.1: Model uncertainties. Purple: global parameters; Blue: parameters used to create the network; Yellow: parameters used in the awareness process; Red: parameters used in the commitment process; Green: parameters used in the target setting process

Uncertainty	Type	Range	Description
sigma	float	[0.01-0.1]	See Table on Agent Parameters 3.1
alpha	float	[0.01-0.20]	See Table on Model Parameters 3.2
beta	float	[0.01-0.20]	See Table on Model Parameters 3.2
gamma	float	[0.01-0.20]	See Table on Model Parameters 3.2
delta	float	[0.005-0.10]	See Table on Model Parameters 3.2
rewiring_frequency	integer	[1-36]	See Table on Model Parameters 3.2

¹Note that EMA workbench uses the term uncertainties instead of parameters. From here onwards the two terms are used to mean the same thing. The term uncertainty is mainly used to describe the parameters that are involved in the sensitivity analysis.

aware_update_step	float	[1-30]	See Table on Agent Parameters 3.1
companies_turn_aware_	float	[1-3]	See Table on Model Parameters 3.2
steps_per_round	float	[1-30]	See Table on Model Parameters 3.2
shareholder_pressure_	float	[0.1-2.0]	See Table on Model Parameters 3.2
manager_pressure_coef	float	[0.1-2.0]	See Table on Model Parameters 3.2
employee_pressure_coe	float	[0.1-2.0]	See Table on Model Parameters 3.2
market_pressure_coeff	float	[0.1-2.0]	See Table on Model Parameters 3.2
manufacturing_coeffic	float	[0.1-2.0]	See Table on Model Parameters 3.2
non_manufacturing_coe	float	[0.1-2.0]	See Table on Model Parameters 3.2
pressure_threshold	float	[1-20]	See Table on Model Parameters 3.2
motivation_threshold	float	[1-20]	See Table on Model Parameters 3.2
max_comm_duration	integer	[12-48]	See Table on Model Parameters 3.2
meetings_per_year	integer	[1-20]	See Table on Agent Parameters 3.1
pres_mot_evaluation	string	{"product", "sum", "se- rial"}	The default evaluation of pressure and motivation before comparing to the threshold is multiplication of the values and the thresholds. This is to check if a serial (two thresholds one after the other) or addition makes a difference.
internal_target_range	list	{(0,0.5), (0,1), (0.5,1)}	See Table on Model Parameters 3.2
work_rate	float	[0.1,1.0]	See Table on Agent Parameters 3.2

The outcomes of interest are the following:

1. **final_aware_total_percent**: The percentage of companies that after 60 steps (2015-2020) end up becoming aware.
2. **final_committed_total_percent**: The percentage of companies that after 60 steps (2015-2020) commit to setting a SBTi target. The estimated percentage in 2020 is 20% (Appendix A.1).
3. **final_target_set_total_percent**: The percentage of companies that after 60 steps (2015-2020) set a SBTi target. The estimated percentage in 2020 is 12% (Appendix A.1).
4. **average_time_to_set_target**: The average time taken for companies that have committed to set a target. The estimated time in 2020 is 6.4 months (Appendix A.4).

4.3.1 Open exploration

Feature Scoring

The first method used for the open exploration of the model is feature scoring. This is a less computational intensive substitute for the SOBOL (more in Section 4.3.2) in order to get a first idea on which are the most significant inputs for each of our outputs.

The method generates a score for each uncertainty indicating its importance. The values are normalised to sum up to 1. The higher the score the stronger the influence on the outcome. The scores of the uncertainties for the outcomes `final_aware_total_percent`, `final_committed_total_percent` and `final_target_set_total_percent` are presented in figure 4.1.

In all three outcomes, the most important uncertainty is the `aware_update_step` and the second is `steps_per_round`. As previously explained, the `aware_update_step` parameter defines the frequency with which the awareness process through interaction with neighbour take place while the `step_per_round` defines the frequency that SBTi has campaigns to increase awareness of its existence. These results imply that parameters directly used in the awareness process have a huge impact in all three outcomes. The model's structure is serial i.e. a company needs to be aware in order to become committed and it needs to be committed in order to be able to set a target. Thus, the results indicate that the initial step's parameters influence the trajectory of progress of the other outcomes down the line.

Furthermore, factors such as `meetings_per_year`, `pressure_threshold` and `motivation_threshold` even though they have low significance for the awareness percentage outcome, they are important for commitment and target setting percentages. These are all factors that are involved in the commitment process (Section 3.2.4). The thresholds are defining the limits needed to be overcome for a company to commit, thus it is expected that they are significant for the commitment process. Since companies need to have a committed status to set a target, these parameters also impact the target-setting outcome, as it is downstream from the commitment process.

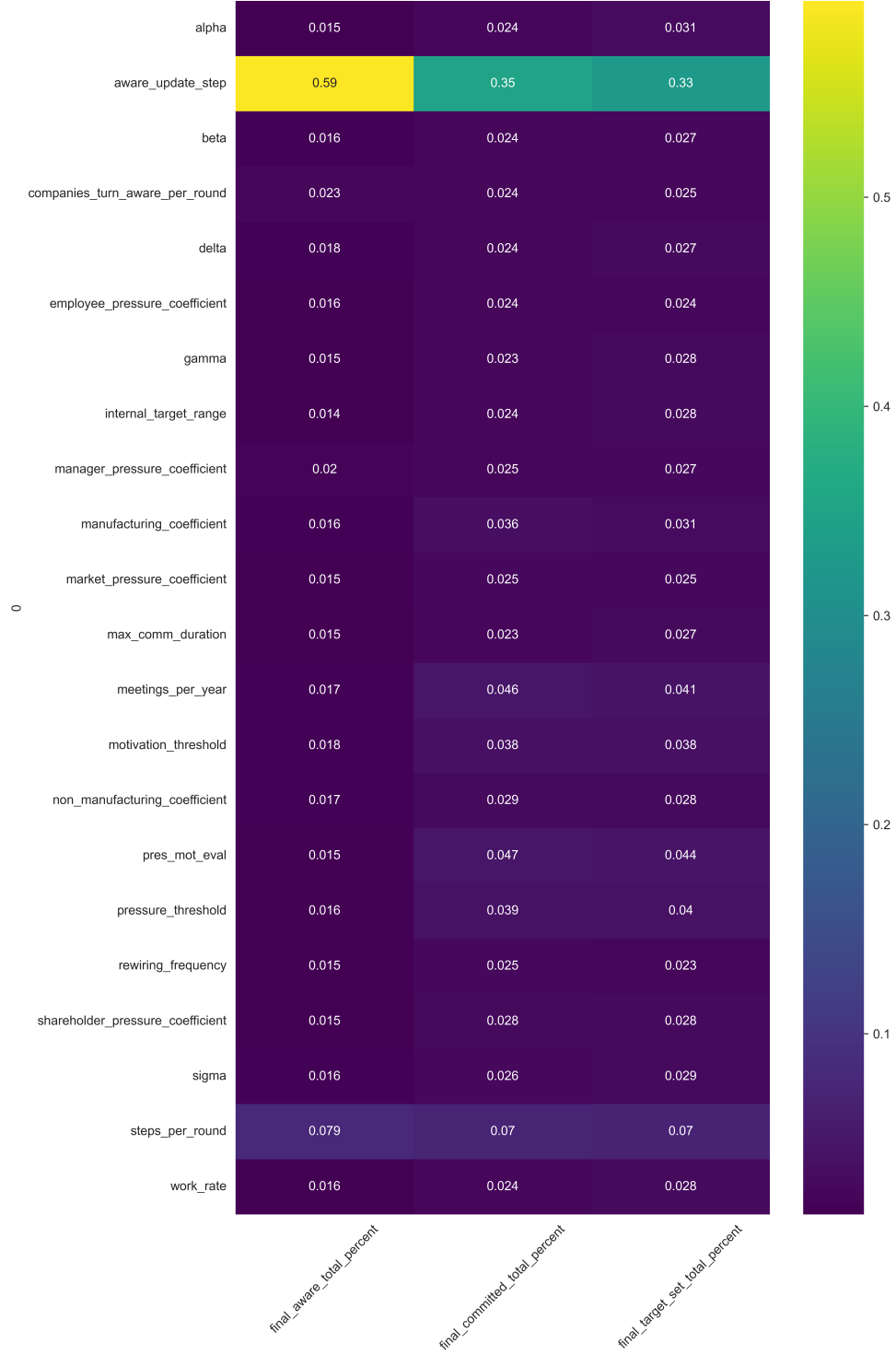


Figure 4.1: This figure illustrates the feature scoring for various uncertainties affecting the outcomes `final_aware_total_percent`, `final_committed_total_percent`, and `final_target_set_total_percent`. The scores are normalized to sum to 1, indicating the relative importance of each feature in influencing these outcomes. The `Aware_update_step` uncertainty is significantly the most influential uncertainty for all the outcomes.

Patient Rule Induction Method

The Patient Rule Induction Method (PRIM) is a scenario discovery method used to identify combinations of uncertainty and/or policy values that lead to specified outcomes. It seeks regions with a high density of the outcome of interest by iteratively peeling away areas from the parameter space that have lower density or do not include the outcome of interest (Bryant & Lempert, 2010). This peeling away process is based on two metrics: the density, which is the ratio of the data points that lead to the outcome of interest inside the 'box' (parameter space left after each iteration of peeling) and the coverage which is the ratio of all data points leading to the outcome of interest that are left inside the box and were not peeled away. The PRIM was used to find scenarios for the following three outcomes that are grounded in reality:

- Average time to set target- Scenario discovery for values between 5 and 7 months. Estimated time is 6.4 months.
- Commitment percentage: Scenario discovery for values between 10% and 30%. Estimated to be 20% by 2020.
- Set target percentage: Scenario discovery for values between 1% and 20%. Estimated to be 12% by 2020.

The importance of uncertainties towards the outcome of interest is derived from the qp values associated with each parameter. The smaller the qp value, the stronger the evidence against the null hypothesis, i.e., the parameter has a significant impact on the outcome of interest.

Starting with the target outcomes for average time (5 to 7 months), the trade off curve is plotted (figure 4.2a) showing the number of dimensions (i.e. uncertainties) that were used to peel away from the parameter area to increase the density of outcomes of interest above 0.6 (out of 1 which means all the points) while keeping the coverage as large as possible. This led to a density 0.636 and coverage of 0.217. This implies that the outcomes of interest could come from very different combinations of results, showing a high complexity of the system. Upon inspection of the most important uncertainties (Table 4.2 and figure 4.2b), there were some key takes that need to be noted. The most significant uncertainty (lowest qp value) was the `internal_target_range` and the value that best suited the outcome of interest is the range [0-0.5]. This indicates that with higher ranges [0-1] and [0.5-1] the average time tends to be shorter than 5 to 7 months. The `work_rate` has a high significance which implies what should be expected with this uncertainty. Companies with work rates 0.24 to 0.84 finish setting a target within the range of 5 to 7 months.

A very unexpected outcome here is the significance in peeling away the smaller values of `employee_pressure_coefficient`. It could be a variety of reasons, such as that having employee pressure affected by the leading dimension (see section 3.2.4 could mean that countries with low leading value don't manage to pass the threshold to commit and there might be a relation of countries having low leading dimension and high deciding or scheduling dimension leading to an increase in the final average time. This

could only be answered with a closer look on this specific instance. The key point to take from this is the complexity and interdependence of the variables.

Table 4.2: PRIM results for the average time to set a target within a range of 5 to 7 months. The table highlights key uncertainties affecting this outcome, with small qp values indicating higher significance. NaN values indicate that there was no peeling from that end of the range. Uncertainties that are not present were not significant enough to be used in the peeling process. This table complements Figure 4.2b by providing precise values for easier interpretation.

Uncertainties	min	max	qp value for min	qp value for max
aware_update_step	1.0	26.0	NaN	0.114986
pressure_threshold	1.01529	18.279523	NaN	0.275470
non_manufacturing_coefficient	0.101098	1.824662	NaN	0.342883
internal_target_range	(0, 0.5)	(0, 0.5)	0.000003	NaN
employee_pressure_coefficient	0.630038	1.998972	0.014472	NaN
work_rate	0.236275	0.839817	0.029032	0.084790
max_comm_duration	15	48	0.243086	NaN
alpha	0.030903	0.199946	0.255901	NaN
gamma	0.031523	0.19987	0.290052	NaN
meetings_per_year	2	18	0.362298	0.325118
steps_per_round	2	24	0.380147	0.057835

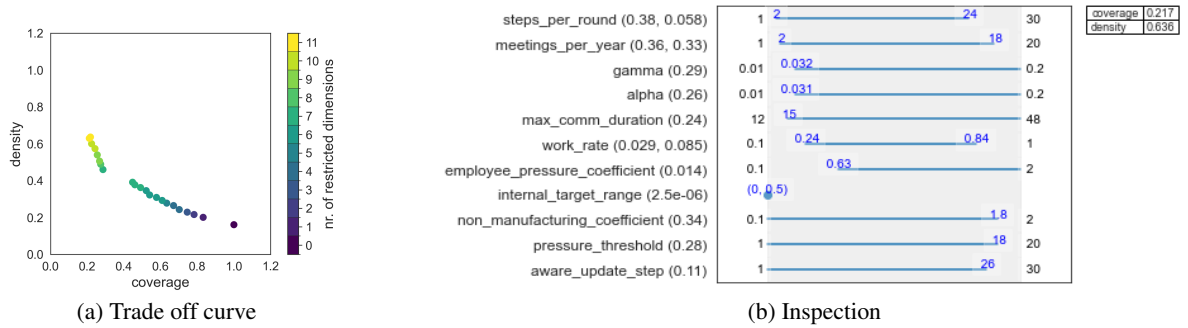


Figure 4.2: The visualisation of PRIM results for average time between commitment and setting a target within 5 to 7 months. Sub-figure (a) shows the trade-off curve between density and coverage of outcomes, aiming for high density above 0.6 and maximum coverage. Sub-figure (b) inspects the most significant uncertainties affecting after 11 uncertainties were used to increase the density of desired outcomes. It mirrors the table presented above.

The second outcome of interest, commitment percentages between 10% and 30%, also has a weak concentration of combination of parameters, with the best scenario discovery giving a density of 0.557 and a low coverage of 0.286 signaling again that the desired outcomes could arise from a vastly different combination of uncertainties. The inspection of the most important uncertainties (Table 4.3 and figure 4.3b), gave us some key findings on the most significant uncertainties. The lowest qp value is given by the reduction of the

steps_per_round to maximum 18. This uncertainty reflects on the speed of awareness increase due to SBTi campaigning. This indicates that higher values return percentage of commitment outcomes below the desired outcome. The awareness_per_step which dictates the frequency of companies becoming aware from peers is also significant, showing once again that awareness process significantly affects the commitment percentages. The parameter pressure_threshold is significant which is reasonable since it affects the number of companies that become committed. The additional parameter pres_mot_eval which defines how the motivation and pressure variables (the default is product) is also a notable inclusion here. This means that the decision to treat these two variables as multiples to be compared to a threshold significantly affects the outcome of the model.

Table 4.3: PRIM results for the commitment percentages between 10% and 30%. Small qp values indicate uncertainties with high importance towards the outcome of interest. NaN values indicate that there was no peeling from that end of the range.

Uncertainties	min	max	qp value min	qp value max
steps_per_round	1.0	18.0	NaN	0.004781
aware_update_step	1.0	22.0	NaN	0.044109
pressure_threshold	1.01529	16.696478	NaN	0.069151
manager_pressure_coefficient	0.100296	1.712896	NaN	0.295530
shareholder_pressure_coefficient	0.101525	1.815598	NaN	0.295530
meetings_per_year	1.0	18.0	NaN	0.379558
pres_mot_eval	{serial, sum}	{serial, sum}	0.010214	NaN
employee_pressure_coefficient	0.634225	1.998972	0.025783	NaN
delta	0.025695	0.094678	0.118870	0.221313
max_comm_duration	17	48	0.221313	NaN
beta	0.027257	0.199953	0.334680	NaN
rewiring_frequency	5	36	0.374547	NaN

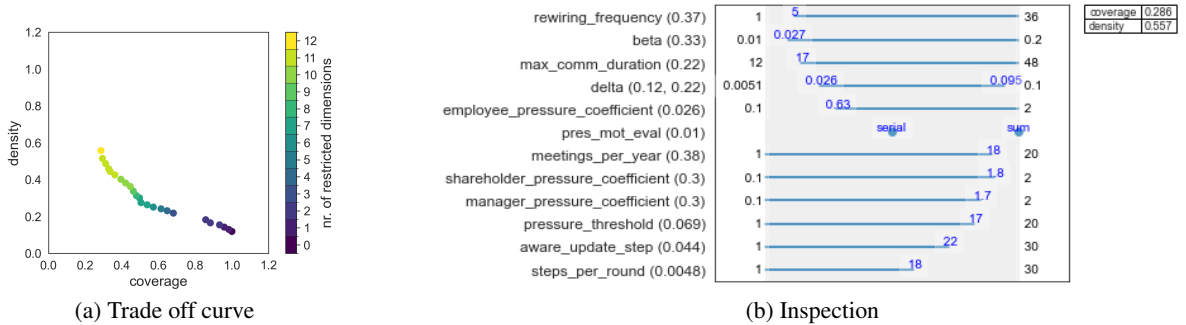
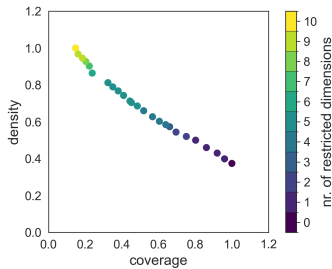


Figure 4.3: Visualisation of PRIM results for commitment percentages between 10% and 30%. Sub-figure (a) presents the trade-off curve, showing the balance between density and coverage of outcomes. Sub-figure (b) inspects the most significant uncertainties affecting after 12 uncertainties were used to increase the density of desired outcomes. It mirrors the table presented above.

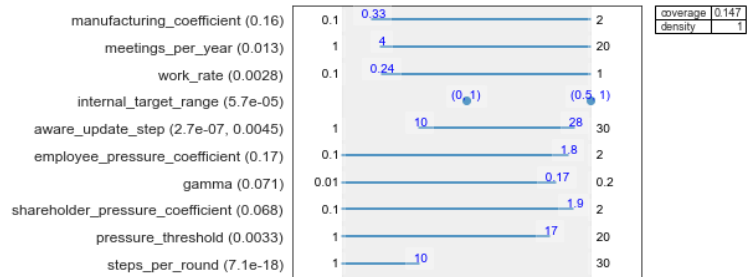
The final outcome was target setting percentages between 0% and 20%. The trade off curve this time gave high density (1) but very low coverage (0.147). This means that PRIM did find a parameter space with only desired outcomes but most of the desired outcomes lied outside this parameter space. This means that target setting percentages predominantly lie between 0 and 20% with very few reaching higher percentages. The key point of this evaluation is that the most important uncertainties that were present in the significant uncertainties regarding commitment percentages and average time are present in this desired outcome too (i.e. steps_per_round, pressure_threshold, aware_update_step and internal_target_range, aware_update_step and steps_per_round). Furthermore, the work_rate and internal_target_range become are very significant which is understandable due to their direct impact on the speed at which a committed company moves towards submission of a target.

Table 4.4: PRIM results for the target setting percentages between 0% and 20%. Small qp values indicate uncertainties with high importance towards the outcome of interest. NaN values indicate that there was no peeling from that end of the range.

Uncertainties	min	max	qp value min	qp value max
steps_per_round	1.0	10.0	NaN	7.137361e-18
pressure_threshold	1.01529	16.791363	NaN	3.316572e-03
shareholder_pressure_coefficient	0.101525	1.864502	NaN	6.832640e-02
gamma	0.01015	0.173433	NaN	7.132509e-02
employee_pressure_coefficient	0.100432	1.822704	NaN	1.744393e-01
aware_update_step	10.0	28.0	2.684286e-07	4.452881e-03
internal_target_range	{(0.5, 1), (0, 1)}	{(0.5, 1), (0, 1)}	5.699969e-05	NaN
work_rate	0.242913	0.999761	2.785114e-03	NaN
meetings_per_year	4	20	1.312878e-02	NaN
manufacturing_coefficient	0.331892	1.998273	1.647312e-01	NaN



(a) Trade off curve



(b) Inspection

Figure 4.4: Visualisation of PRIM results for set target percentages between 0% and 20%. Sub-figure (a) presents the trade-off curve, showing the balance between density and coverage of outcomes. Sub-figure (b) inspects the most significant uncertainties affecting after 10 uncertainties were used to increase the density of desired outcomes. It mirrors the table presented above.

4.3.2 Global Sensitivity Analysis

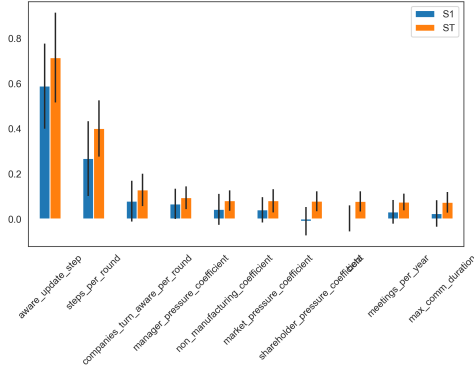
SOBOL method

The SOBOL method is a variance-based GSA method. The advantage of this method is that it considers both first-order and total-order effects towards the behaviour of the model, by providing indices that quantify the contribution of each input parameter (uncertainty). The first-order indices represent the reduction of the output variance that would occur, on average, if the parameter is fixed. The total-order indices represent the combined expected reduction in output variance if an input, along with all its interactions, could be fixed. In other words, the difference between the first- and total-order index of a parameter is that the total-order index also includes the variance by all of the interactions with other parameters (ten Broeke et al., 2016).

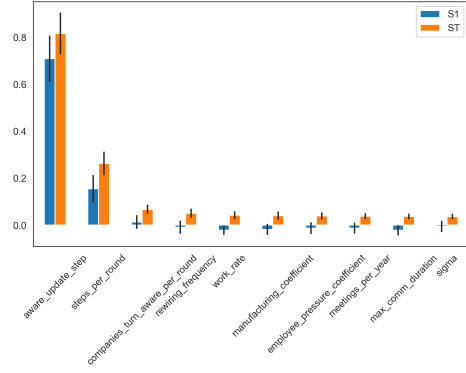
This section is divided in three parts for the three outcomes on which SOBOL was used: awareness percentage, commitment percentage and target setting percentage. Each outcome was run for 100 and 500 companies to check how an increase in companies affect the final results. The SOBOL evaluation was also run only for 1000 iterations. This is much lower than the typical number which is estimated using the equation $N = n \times (M + 2)$, where N is the number of iterations, n is the factor of proportionality (usually 1000) and M is the number of uncertainties (Hadjimichael, 2020). Once again, due to limitations of computational power, a compromise was made.

When considering the awareness percentage outcome (see figure 4.5, the parameters `aware_update_step` and `steps_per_round` emerge as the most influential, as suggested by their comparatively significant total effect indices (ST) (see figure 4.5. The '`aware_update_step`' has the highest first-order effect for this outcome, indicating that its variation alone leads to a great outcome variability. The third highest first-order index comes from the `companies_turn_aware_per_round`. These three uncertainties are the ones that are directly affect the progress of awareness number. Most of the other parameters have slightly positive or even negative first-order indices, suggesting that their independent variation does not contribute significantly to the final outcome. However, they still possess substantial total effect indices, implying significant interactions between parameters. This effect becomes smaller when the agent number is increased to 500 companies (figure 4.5b). At a larger number of companies, the parameters directly affecting awareness increase their significance. This is due to the mechanism that awareness process is implemented. First, at larger numbers the awareness through campaigns is relatively slower due to the fact that the number of `companies_turning_aware` is not relative to the total number of companies. Secondly, awareness through peers is not affected by the amount of peers but takes place randomly.

Moving on to the commitment percentage, `aware_update_step` and `steps_per_round` still dominate as the most impactful parameters (figure 4.6). In this case however, `meetings_per_year`, `motivation_threshold` become much more significant than the third awareness parameter `companies_turn_aware_per_step`. Their total effect indices suggest their significant contribution to



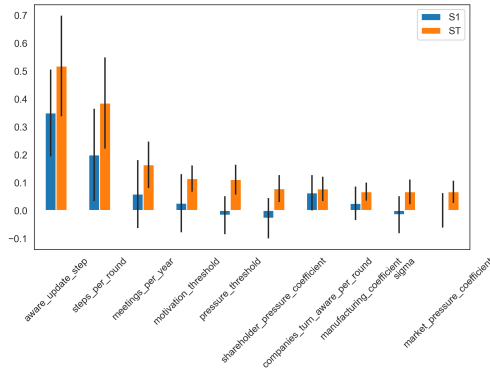
(a) Awareness Percentage- 100 agents



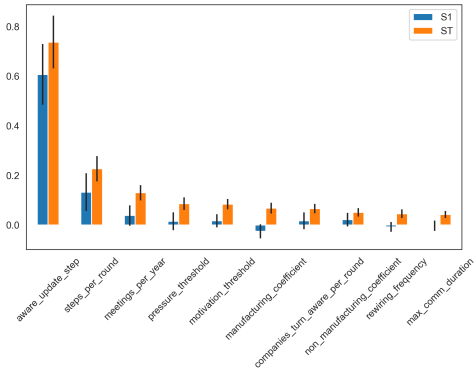
(b) Awareness Percentage- 500 agents

Figure 4.5: SOBOL indices showing the influence of various parameters on the percentage of companies that become aware by the end of the model run. Sub-figure (a) represents the scenario with 100 agents, and Sub-figure (b) represents the scenario with 500 agents. The figure presents both first-order (S1) and total effect indices (ST), with higher values indicating greater influence on the outcome.

the variability of the commitment percentage outcome. These are expected to be the most important parameters affecting the amount of aware companies becoming committed. Several pressure coefficients appear in the 10 most significant parameters which indicate that campaigns focusing on those pressures could potentially lead to a significant increase in companies joining SBTi.



(a) Commitment Percentage- 100 agents

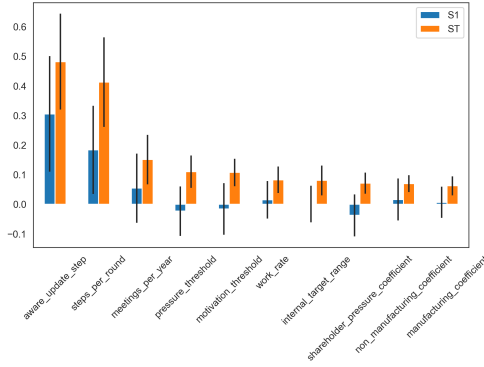


(b) Commitment Percentage- 500 agents

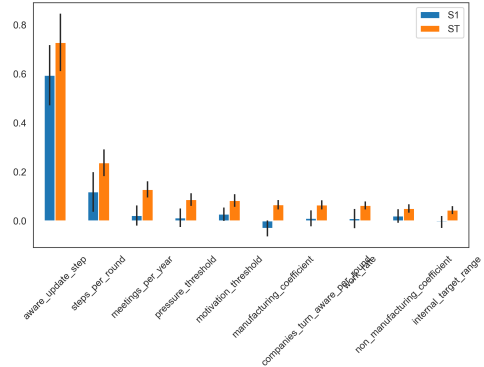
Figure 4.6: SOBOL indices showing the impact of various parameters on the percentage of companies committing by the end of the model run. Sub-figure (a) represents the scenario with 100 agents, and Sub-figure (b) represents the scenario with 500 agents. Both first-order (S1) and total effect indices (ST) are presented, with higher values indicating a greater influence on the commitment percentage outcome.

Finally, the target setting percentage again is influenced vastly by `aware_update_step` and `steps_per_round`, but in a lower extent than the previous two outcomes (see figure 4.7). The `work_rate`

and `internal_target_range` which are used in the target setting process enter the top 10 influential parameters due to a higher total effect index even though they remain very low in first-order index. This indicates that their interaction with a more preferable set of parameters affecting the awareness, they become significant in the final outcome of the set target percentage.



(a) Setting Target Percentage- 100 agents



(b) Setting target Percentage- 500 agents

Figure 4.7: SOBOL indices showing the impact of various parameters on the percentage of companies setting a target by the end of the model run. Sub-figure (a) represents the scenario with 100 agents, and Sub-figure (b) represents the scenario with 500 agents. Both first-order (S1) and total effect indices (ST) are presented, with higher values indicating a greater influence on the target setting percentage outcome.

Comparing the results across all three outcomes, it becomes clear that `aware_update_step` and `steps_per_round` are consistently the most influential parameters. The parameters that tend to be in the top 10 mix are directly associated with the calculations of each process. It would have been beneficial to run SOBOL again with a small variance for the parameters affecting awareness to get a clearer picture of the parameters that become more significant after a company becomes aware, however due to lack of time, the parameter setup is based on these results. The main take then is that for our experiments with 2233 the awareness parameters are the most significant ones to calibrate. The `pressure_threshold`, `motivation_threshold` are the most significant parameters used in the commitment process. Finally, `internal_target_range` and `work_rate` were the most significant parameters in the target setting process. These were the parameters that were varied in the next section.

4.4 Parameter Setup

In this section, the parameter setup for the ABM model is explained. This step is important in order to calibrate the model to represent results close to the reality for the years 2015-2020.

This is done by varying the most significant parameters which were chosen based on the sensitivity analysis outcomes. The uncertainties which were identified as significantly affecting our model's behavior are

rewiring frequency, aware update step, steps per round, pressure threshold, motivation threshold, internal target range, and work rate. The rest of the parameters are kept constant, and their values were chosen based on the acceptable ranges that PRIM provided or from literature (e.g., meetings per year, which were calculated to be 10, and pressure coefficients taken from Wang et al., 2020). Their values can be found in Table 5.1.

The optimization tool used is the platypus-opt from EMA workbench which identifies the optimal parameter configurations. For our specific task, platypus-opt was used to explore combinations of our key parameters and find those sets that produced the desirable outcomes of 6.4 months average time, 20% commitment percentage and 12% set target percentage for the total of 2233 companies. This time the full number of high-impact companies is used since the goal is for the model to reflect the real values. The platypus-opt optimization was set to run for 250 function evaluations (nfe). The number of function evaluations refers to the total number of times the optimization function occurs during the evaluation. The larger the nfe, the more thoroughly the parameter space is explored. However, this comes at the cost of computational resources and time. This led to a compromise with a relatively low number of evaluations in order to run the model with the full number of high-impact companies. It's important to note that the limited number of function evaluations could potentially impact the robustness of our results, making them more exploratory than confirmatory in nature. This is because the fewer the number of function evaluations, the less thoroughly the optimization algorithm can search through the parameter space. This can lead to solutions that are locally but not globally optimal.

Platypus-opt also uses an epsilon value which is a parameter that dictates the granularity at which the parameter space is explored. Lower epsilon values will result in a more thorough, finer-grained exploration of the objective space, but may require more function evaluations to converge (Kwakkel, 2023). The chosen value was 0.01.

The optimization process returned 6 potential parameter sets, which are listed in Table 4.5. In order to choose the most suitable set for our experimentation and results, the three outcomes were treated as equally important, a methodological choice aimed at ensuring a balanced consideration of all key performance indicators. The solution with the closest outcomes to the desired values was Solution 2. The parameter values for this solution are included in Table 5.1.

Table 4.5: Optimized Solutions from Platypus-Opt: This table shows six different sets of optimized parameters (Solutions 1-6) identified by the platypus-opt tool from EMA workbench. Each solution represents a unique combination of the most significant parameters that were found to return the three desired outcomes (20% commitment, 12% set targets and 6.4 months between commitment and setting a target) . The rows ‘final_committed_difference’, ‘final_target_set_difference’, and ‘average_time_to_set_target_difference’ represent the deviation between the optimization objective and the actual outcomes achieved by each solution.

Solution	1	2	3	4	5	6
rewiring_frequency	25	13	17	23	13	9
aware_update_step	17	3	4	5	28	5
steps_per_round	7	7	7	7	7	3
pressure_threshold	3.61	9.03	8.26	10.85	6.71	8.61
motivation_threshold	2.36	7.73	8.44	3.68	7.47	7.54
internal_target_range	(0, 0.5)	(0, 0.5)	(0, 1)	(0, 0.5)	(0.5, 1)	(0, 1)
work_rate	0.76	0.47	0.69	0.53	0.37	0.29
final_committed_difference	0.19	0.01	0.02	0.03	0.20	0.02
final_target_set_difference	0.12	0.02	0.01	0.01	0.12	0.03
average_time_to_set_target_difference	0.04	0.31	2.73	0.15	0	0.12

Chapter 5

Experiments and Results

This chapter focuses on the final step of our ABM modelling process (explained in section 1.2.4); the experimentation step. The previous chapter has resulted in a set of values for the parameters of the model that satisfy the desired outcomes that represent reality. As previously elaborated, parameter tuning only took place for the most significant parameters while the rest were given values that lied within the range that satisfied the open exploration (see section 4.4). The parameters are provided in Table 5.1.

The first section of this chapter focuses on the findings of the base scenario. The base scenario is the evolution of the model from the establishment of the SBTi in May 2015 until May 2020, which is the last known numbers of companies that are committed or set target before the beginning of CDP high-impact campaigns began. The characteristics of the companies that succeed or failed to join are looked more closely.

The second section provides the experiments made using the fine-tuned model to make near future projections from September 2021 (step 64 which is the the beginning of the CDP high-impact campaigns) until May 2025. The section provides 2 sets of scenarios on actions that SBTi could employ at the beginning of 2020. The first set contains six scenarios to explore the effects of different campaigns on shareholder, manager, employee, and market pressure. Each scenario is further divided into two experiments, representing moderate and high levels of the targeted pressures. In these scenarios, a multiplier is employed on the different pressure values calculated (equations in Section 3.2.4).

The second set provides scenarios more specific on strategies that the SBTi could implement. The first is increasing the market pressure to join the SBTi by facilitating a promotion/reach of the companies that commit so as to increase the reach and pressure within the high-impact companies. The second scenario is an increase of the deadline to set a target after the companies commit to 48 months to facilitate slow-movers catching up with the process.

The goal of this chapter is to shed light on the final two sub-questions: "How does the combination of these factors (questions above) affect the uptake of companies?" and "What are potential strategies that SBTi can implement to speed its uptake?"

5.1 Base Scenario

Having concluded in a parameter set that could provide outcomes close to reality for the period 2015 to 2020 (Table 5.1), the next step is to test the insights of such a model. The model is run with the total number of high-impact number of companies (2233) for 60 steps (May 2015 to May 2020) for 50 iterations. The mean results and standard errors are collected for each of the desired outcomes. The base scenario is essentially giving insights on what company characteristics are identified as more probable in committing and setting targets to SBTi, before the focused campaigns started in September 2020 (month 64).

Table 5.1: Parameter Setup. Purple: global parameters; Blue: parameters used to create the network; Red: parameters used in the awareness process; Yellow: parameters used in the commitment process; Green: parameters used in the target setting process. Note that an extra group (orange) provides the levers used for the experiments (see section 5.2). The description for the parameters can be found in Section 3.2.1. The rest of the parameters were taken from literature (see Section 3.2.1

Parameter	Value	Source
sigma	0.025	Normal distribution value. Chosen based on PRIM (section 4.3.1)
alpha	0.15	Chosen based on PRIM (section 4.3.1)
beta	0.15	Chosen based on PRIM (section 4.3.1)
gamma	0.15	Chosen based on PRIM (section 4.3.1)
delta	0.05	Chosen based on PRIM (section 4.3.1)
rewiring_frequency	13	Chosen based on parameter tuning (section 4.4)
aware_update_step	3	Chosen based on parameter tuning (section 4.4).
companies_turn_aware_per_round	1	Chosen based on PRIM (section 4.4).
steps_per_round	7	Chosen based on parameter tuning (section 4.4).

pressure_threshold	9.02	Chosen based on parameter tuning (section 4.4).
motivation_threshold	7.73	Chosen based on parameter tuning (section 4.4).
work_rate	0.47	Chosen based on parameter tuning (section 4.4).
internal_target_range	[0.0, 0.5]	Chosen based on parameter tuning (section 4.4).
manager_pressure_lever	1.0 (default)	Used as a multiplier in equation 3.4.
shareholder_pressure_lever	1.0 (default)	Used as a multiplier in equation 3.3.
employee_pressure_lever	1.0 (default)	Used as a multiplier in equation 3.5.
market_pressure_lever	1.0 (default)	Used as a multiplier in equation 3.7.

The progress of number of companies turning aware, becoming committed and setting a target over time is presented in figure 5.1. The desired outcomes as mentioned in the Sensitivity analysis chapter are: 20% commitment and 12% setting a target. The model results give a satisfactory representation of the commitment rate with the average being 20.38% and standard error 0.61% which means that the desired outcome lies within the standard error. The model set target percentage $11.30\% \pm 0.41\%$ slightly below the desired outcome. The last desired outcome that was in our scope in sensitivity analysis was the average time from committing until setting a target. The model returned 6.85 ± 0.05 months which is slightly higher than the estimated value which was 6.4 months. These results confirm that the parameter tuning has provided us with a model that satisfies the outcomes that was tuned to satisfy.

The model also predicts that $100\% \pm 0.00\%$ of companies become aware of the existence of the SBTi by step 60. This means that although model is very sensitive to the awareness process at the beginning of the run, by step 60 all companies reach the state of being aware and different dynamics become important for the rest of the run.

Sectoral Characteristics

The first set of characteristics of the companies are connected to their sector. Table 5.2 compares the model's outcomes for the percentage of companies that are committed or have set a target for climate action, against the SBTi 2021 Report's data for each sector. The sectors are further classified into three types based on their

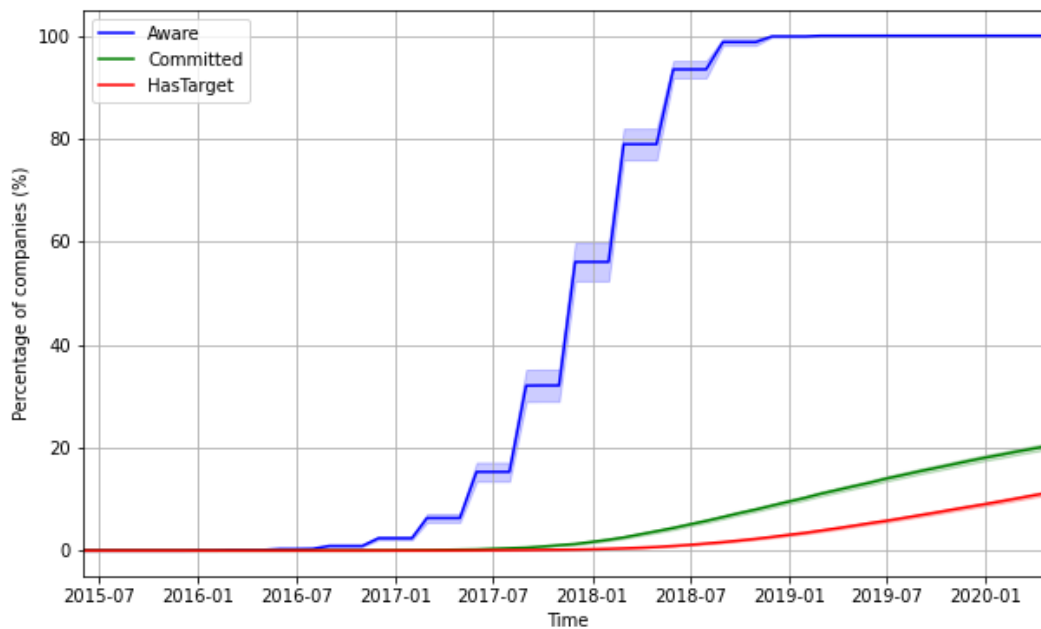


Figure 5.1: Number of companies becoming aware, committed and setting a target. The run was with 2233 companies from May 2015 until May 2020. At the last step $100\% \pm 0.00\%$ turning aware, $20.38\% \pm 0.61\%$ becoming committed, and $11.30\% \pm 0.41\%$ setting a target

manufacturing characteristics: Manufacturing Type, Non-Manufacturing Type, and Both. The classification of the sectors was done based on estimates of their core activities as detailed in the Appendix Section A.2.

The commitment process of the companies (explained in Section 3.2.4) has different weights for manufacturing and non-manufacturing types. The manufacturing sectors are assigned a lower `sector_factor` value compared to non-manufacturing sectors, leading to lower stakeholder pressure and consequently fewer commitments in manufacturing sectors. The sectors that have both manufacturing and non-manufacturing processes were given the average value of the other two.

Overall, the model predicts that the Manufacturing sectors are less likely to commit compared to the Non-Manufacturing. This aligns with literature by Wang et al., 2020 the real-world challenge of driving commitment in sectors that have more carbon-intensive operations. However, the model underestimates the commitment in the sectors 'Food beverages and agriculture' and Manufacturing, where real-world figures are significantly higher. This discrepancy could be attributed to the model's simplifications, or potentially due to sector misclassification in the appendix, which could also explain why sectors classified as Both manufacturing and non-manufacturing are less likely to commit than Manufacturing. It has to be noted that within sector Other labeled as "Other," Oil and Gas is included which is a very carbon-intensive sector and was classified as Both ((SBTi, 2022), p.).

As a further step to quantify the accuracy of the model's predictions, two metrics were employed: the weighted Pearson correlation coefficient r and the Mean Absolute Error (MAE). The Pearson r measures the linear relationship between the model's outcomes and the real-world data taken from the SBTi Report. It takes values from -1 to 1 indicating a stronger negative and positive correlation respectively. In order to take into consideration that some sectors were more represented a weight was included based on the number of companies per sector. The second metric, MAE, provides an average of the absolute errors between the model's values and the actual percentages. Thus lower value indicates that the model outcomes are closer to SBTi report results.

The sector results showed no correlation for both committed and set target results (0.00%) and high MAE (6.4 % and 4.5 % respectively) when compared to the SBTi report data. However, the removal of the outlier sector 'Food beverages and agriculture' improved these metrics. The Pearson r for the percentage of companies committed per sector increased to 0.294 and the MAE decreased to 0.046. For companies with set targets per sector, Pearson r increased to 0.252 and the MAE decreased to 0.039. These figures indicate a positive weak relationship.

In the next figure 5.2, the distribution of companies in the given sectors and the number that end up aware, committed or with a target is presented. The distribution aligns with the given SBTi distribution in figure 2.3. The error bars in the figure denote the standard deviation to give an idea about how much individual simulation runs differ from the average. The low variability could suggest that the model is capturing some key dynamics, even if it's an exploratory model.

Table 5.2: Sectors Committed and Set Target

Sectors	Model			SBTi Report 2021		
	Committed (%)	Set (%)	Target	Committed (%)	Set (%)	Target
Transportation services	24.4	13.2		26.3	18.8	
Services+ Financial services	24.2	13.6		31.9	16.3	
Infrastructure	21.8	12.4		15.8	8.6	
Other + Apparel + Hospitality + Retail	21.5	12.0		20.9	9.4	
Food beverages and agriculture	18.1	9.6		64.4	30.8	
Manufacturing	17.3	9.6		29.9	16.0	
Power generation	17.2	9.4		19.6	12.0	
Materials	17.2	9.4		22.5	10.5	
Non-Manufacturing Type	24.3	13.5		30.6	16.8	
Both	21.6	12.1		19.6	9.2	
Manufacturing Type	17.3	9.5		29.1	15.0	

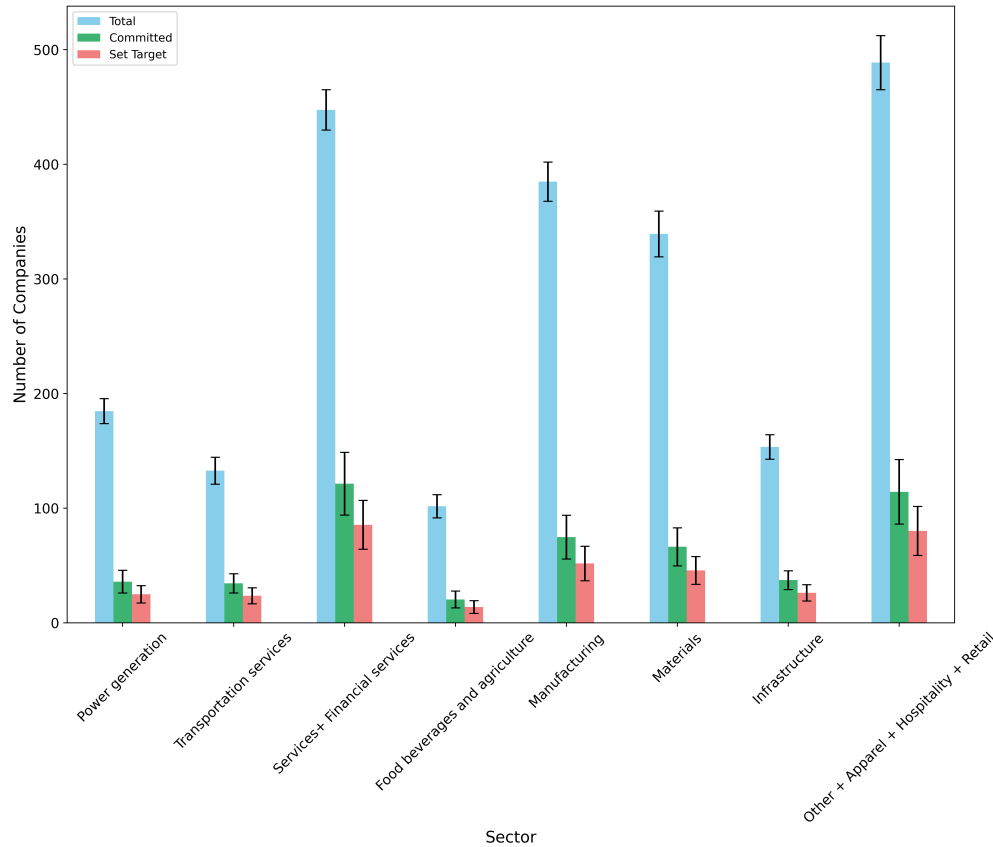


Figure 5.2: Sector distribution. Error bars show the standard deviation

Finally, Table 5.3 provides the predictions of the model regarding the amount of emissions that ends up in companies that are committed or set a target. The model takes emission percentage of each sector (Appendix A.2) and multiplies it by the total emissions of the high-impact companies which is 13500 Mt (Oliver Wyman, 2021, p.26). The average emissions per company for each sector is then found by dividing the emissions portion by the number of companies of each sector. When the model is run the total emissions of committed companies and companies with targets is calculated. The committed companies and those that have set targets emit less per company on average as compared to the overall model's average emissions per company. This indicates that the model captures the key trend less carbon intensive companies are more likely, which also aligns with the classification of sectors into manufacturing and non-manufacturing.

Table 5.3: Emission Characteristics of Committed and Set Target Companies

	No. Companies	Total Emissions (Mt)	Emissions per Company (Mt)
Committed Companies	504	2862.9	5.7
Companies with Set Targets	352	1983.0	5.6
All companies	2233	13500	6.1

Country Characteristics

The next group of characteristics that are analysed are based on the country of origin. These include the culture dimensions discussed in Chapter 3 that are used to describe how different dimensions influence the commitment and target setting process. Figure 5.3 presents the 10 most represented countries in the CHIS sample. The model generates populations that align with the percentages presented in the SBTi Report. The countries' commitment and target setting percentages predicted by the model vary significantly. Countries such as China and Japan have similar numbers of high-impact companies in the sample but Japan was more committed companies than China, however ends up having a very low number of set targets.

To evaluate the model's performance concerning committed percentages and target setting percentages per country, weighted Pearson's r and Mean Absolute Error metrics were once again employed. For committed percentages, the weighted Pearson r value was 0.662, indicating a strong linear correlation. This suggests that the model is quite reliable in capturing the general trend of commitment across countries. However, the MAE stood at 12.6%, indicating relatively low accuracy. For target setting percentage, the weighted Pearson r value was 0.46, denoting a moderate positive linear correlation and the MAE was 7%, also indicating a low accuracy.

These values imply a level of effectiveness in the model's predictive capabilities. The high Pearson r value for commitment indicates that the model performs fairly well in capturing the broader trends on how culture affects commitment, however the large average error as shown by the MAE indicates that there are more dynamics at play. The Pearson r for setting a target is lower which could mean that the decisions taken for the culture dimensions affecting the target setting process were less fitting. (Section 3.2.5).

Table 5.4 holds the average scores of the culture dimensions of all the companies, the ones that committed and the ones that set a target. The scores were drawn from the Culture Mapping tool (discussed in the Appendix, section A.3).

Table 5.4: The mean and standard deviation values of the scores cultural dimensions for all companies, companies committed, and companies that have set targets. Values are presented as mean (std)

Cultural Dimensions	Total	Committed	Set Target
Communicating	48.1 (0.8)	42.2 (1.6)	33.1 (1.6)
Evaluating	53.6 (0.5)	49.7 (1.1)	44.2 (1.1)
Leading	56.1 (0.7)	51.6 (1.2)	45.8 (1.3)
Deciding	57.1 (0.5)	55.1 (1.1)	60.0 (0.9)
Trusting	46.3 (0.7)	40.7 (1.4)	33.0 (1.6)
Disagreeing	55.6 (0.5)	51.4 (1.1)	45.4 (1.2)
Scheduling	42.1 (0.6)	38.0 (1.1)	36.7 (1.2)

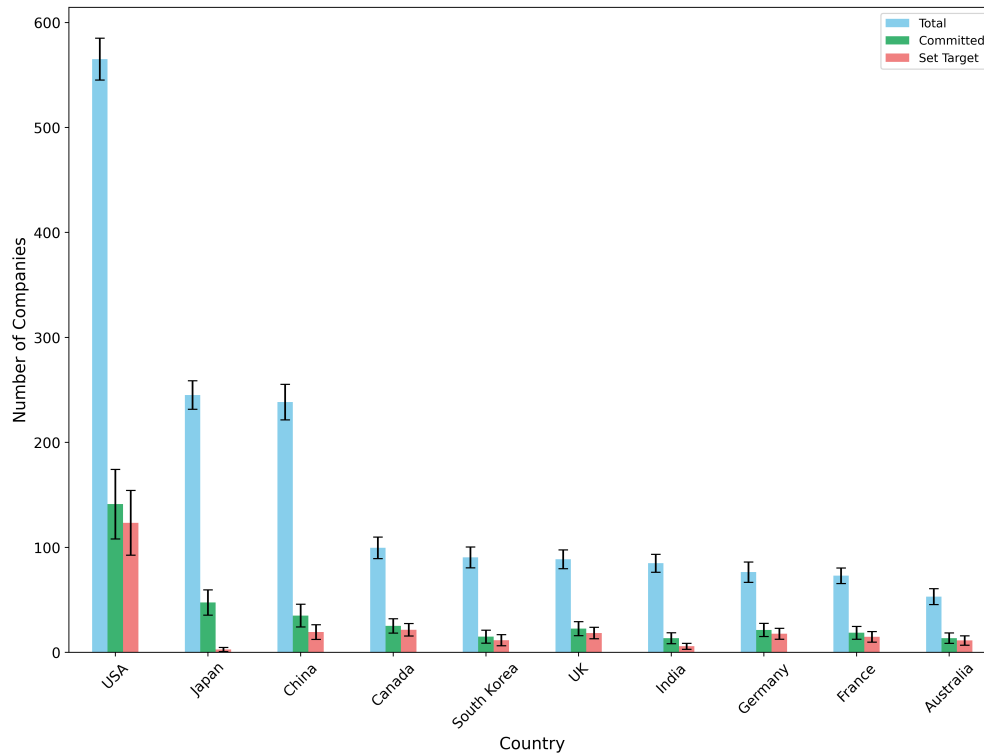


Figure 5.3: Country distribution. Error bars show the standard deviation

For the **Communicating** dimension, both committed and target-setting companies have lower mean scores (42.2 and 33.1) than the total mean (48.1). As explained during the formalisation step, the model uses this dimension in the awareness process. Similar communications scores increase the probability of information passing from one neighbour to the other. This great deviation from the average score, indicates that the model predicts that companies from countries with more straightforward communication norms end up committing and setting targets more. The model's mechanisms do not use this dimension in any way to influence commitment and target setting rate directly. However, looking more closely to the most represented countries, we can see that China which has 230 companies, has a Communicating score of 90 which is much higher than average but only 14.7 % commitment. This could explain why the results are skewed towards smaller communicating scores. Furthermore, it could be an indication that the cultural dimensions by Erin Meyer have correlations between them, thus low communicating scores also tend to relate with other dimension scores that affect commitment rates directly, such as Leading, Trusting etc (see the summary of the dimensions used in Table 5.5. This

The **Evaluating** dimension is a dimension that is not used in the model but once again, a shift towards lower scores for companies that committed or set target is observed (49.7 and 44.2, respectively). This again could be explained due to extremely high scores by some of the most represented countries that have lower commitment and set target than the overall average (Japan with 71 and China 91).

The **Leading** dimension also has committed and target-setting companies scoring 51.6 and 45.8, which is lower than the total mean of 56.1. A low score in the leading dimension, implies a more egalitarian culture in which employees could potentially openly disagree with management and social responsibility actions are more pressed upon the companies. This was implemented in the model's stakeholder pressures and corporate motivations as discussed in the Formalisation step. The model, then predicts this behaviour in its outcomes.

The **Deciding** dimension was used in the target setting process (section 3.2.5). A higher score indicates a top-down culture where decisions are taken by the directors which leads to faster decision-making but slower implementation of the decision due to problem that arise and were not taken into account at the beginning. The model is built with the assumption that a higher score would hasten the submission process. Interestingly, committed companies score slightly lower (55.1) than the average of all the companies (57.1), but companies that have set targets score higher (60.0). Thus the model's outcomes support the initial assumption that setting a target is faster for higher deciding scores even though committed companies have a lower deciding score, which could also be due to interrelations between culture dimensions or specific countries skewing the outcomes as discussed before.

In the **Trusting** dimension, both committed and target-setting companies score significantly lower (40.7 and 33.0) compared to the total mean (46.3). The model uses this dimension in two instances: in corporate individual motivations where task-based (high score) cultures were assumed more beneficial and contrastingly in market pressures (i.e. pressure between competitors, suppliers etc) where relationship-based (lower value) trust creates more pressure. The results thus indicate that the model is more sensitive to the market pressure.

In the **Disagreeing** dimension, committed and target-setting companies also score lower with mean scores of 51.4 and 45.4, respectively, against a total mean of 55.6. This dimension was used as a weight in the shareholder pressure and climate risk awareness. A higher score meant larger weight, representing a more confrontational culture that led higher shareholder pressure and more engagement against the climate risks. The final outcomes support the mechanisms simulated by the model.

Finally, in the **Scheduling** dimension, both committed and target-setting companies show lower mean scores (38.0 and 36.7, respectively) than the total mean (42.1). Scheduling dimension describes the attachment to strict deadlines and was formalised as a dimension that affects both commitment process and set target process. In the commitment process, a higher score in scheduling dimension increased manager pressure and in target setting process in led to a more constant progress towards setting a target (more in section 3.2.5). The final outcomes support the mechanisms simulated by the model.

As a final analysis regarding the country characteristics, the model's prediction as to companies of which country are more likely to fail and set a target within the 24-month deadline after their commitment is explored. The countries with the highest rate of failed companies is presented in Figure 5.4. It has to be clarified that the percentage comes from the total number of companies and not out of the ones that end up

Table 5.5: Culture Dimensions used in the model. The culture mapping scale is between 0 and 100. As discussed in 2.3.1, each dimension is evaluated on an axis between two tendencies. The column Score indicates the direction on the axis that leads to an increased outcome. Green rows indicate dimensions used in the commitment process, red rows indicate dimensions used in the Set Target Process and the yellow row indicates a dimension used in the awareness process.

Process	Dimension	Score	Meaning	Outcome
Employee Pressure	Leading	Low	More egalitarian	Higher pressure
Shareholder Pressure	Disagreeing	Low	More confrontational	Higher pressure
Manager Pressure	Scheduling	Low	Linear (stricter deadlines)	Higher pressure
Market Pressure	Trusting	Low	Relationship-based trust	Higher pressure
Climate risks awareness	Disagreeing	Low	More confrontational	Higher climate risk awareness
Climate reputation	Trusting	High	Task-based trust	Higher importance in climate reputation
Climate leadership	Leading	Low	More egalitarian	Higher importance in climate leadership
Setting a target	Scheduling	Low	Linear (stricter deadlines)	Less uncertainty in working on the submission
Setting a target	Deciding	High	top-down	Faster decision-making
Becoming aware	Communicating	NaN	comparison between companies	If similar values, higher chance of turning aware.

committing. The results show that the model parameters lead to a large number of companies failing coming from Sweden. Japan's percentage is also significant since it is the third most represented country in the CHIS sample with 230 countries.

A closer look into the culture dimensions' scores of the countries that have the highest failing rate showed as expected a clear pattern regarding the **Deciding** and **Scheduling** dimension (Figures 5.5b and 5.5a). The model predicts that scores higher than the average Scheduling score lead to a higher percentage of failed attempts in setting a target after committing. This would mean that the model predicts that countries with flexible timelines are more prone in not completing the submission. The model uses the scheduling score as a weight on the probability of not progressing in the submission at every step/month. The main exceptions are Sweden, Japan and Norway which have a very low Scheduling score. The reason the end up having higher percentage of failed companies could be explained by the extremely low scores in Deciding score.

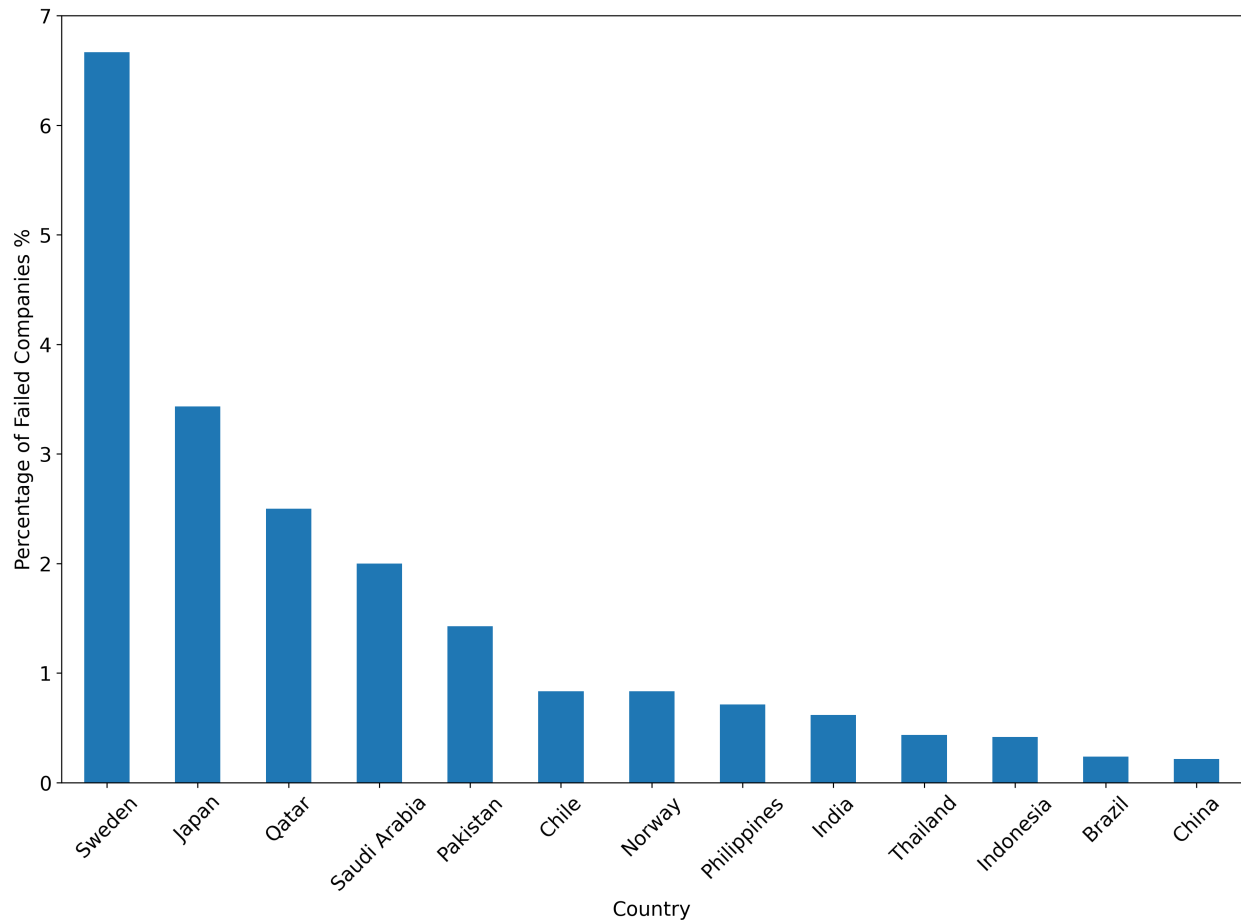
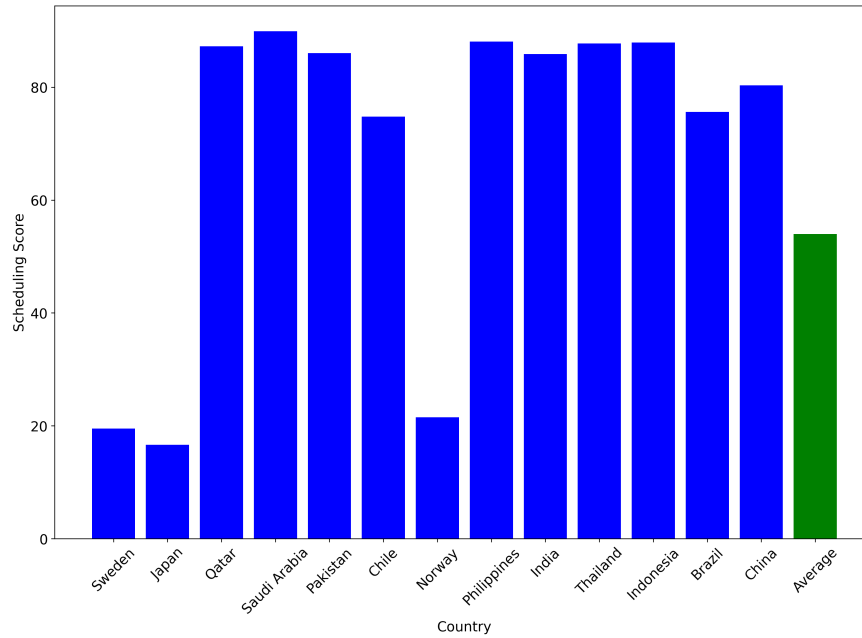


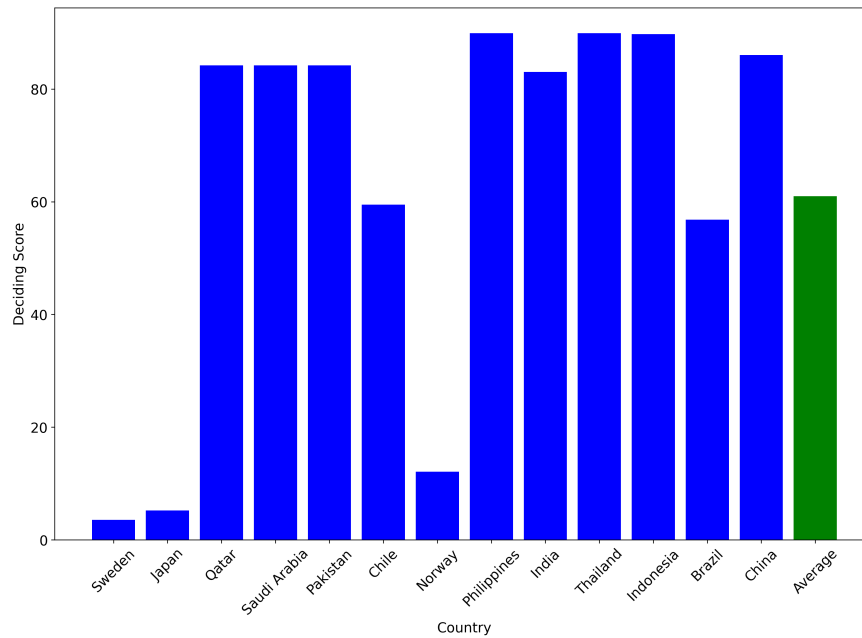
Figure 5.4: The model's average percentage of failed companies per country in the period 2015-2020. The highest 10 countries are presented.

As discussed in Section 3.2.5, deciding dimension is used as a weight on the amount of progress per step. The reasoning was that consensual cultures delay taking decisions and making plans because they place importance in agreement of all stakeholders. There is no public data available on the companies that failed to meet the deadline, thus this proposition cannot be validated, however it does highlight the possibility that companies from specific countries with find it difficult to meet the SBTi demands.

Overall, the base scenario outcomes indicated a moderate to strong correlation between SBTi report and model commitment and set target percentages for the represented countries. This implies that the proposed mechanisms simulating the effect of culture dimensions capture some of the dynamics that dominate the corporate arena.



(a) Scheduling Dimensions



(b) Deciding Dimension

Figure 5.5: The 10 countries with the most failures in meeting the 24-month based on the model outcomes. The two diagrams show how their Deciding and Scheduling scores compare to the average score of those dimensions

5.2 Experiments

As discussed in Section 2.1.3, from September 2020 onwards a high-impact companies campaign was established by CDP in collaboration with SBTi to increase investor/shareholder pressure. Inspired by this specific campaign, several scenarios are developed. The scenarios are implemented in the code by starting a campaign in September 2020 (step 64). The model is then run from May 2015 until May 2025 (108 steps) for 50 runs and the number of commitments and set targets is collected. The mean and standard deviations of all the runs is then calculated.

The **first** set of scenarios multiply the manager (equation 3.4), shareholder (equation 3.3), employee (equation 3.5) and market pressures (equation 3.7) by a certain factor. For each scenario two different experiments are run: one with a multiplier of 5 representing a moderate level of increased pressure and one with a multiplier of 10 representing a high level of increased pressure. A No campaigns scenario and a combination of all the campaign (All campaigns) is also included (see Table 5.6).

Table 5.6: Scenarios and Experiments of Different Campaigns. The numbers represent the factors that are used to multiply the manager (equation 3.4), shareholder (equation 3.3), employee (equation 3.5) and market pressures (equation 3.7).

Scenario	Experiment	Shareholder Pressure	Manager Pressure	Employee Pressure	Market Pressure
No Campaigns	Experiment	1	1	1	1
Shareholder Campaign	Experiment 1	5	1	1	1
	Experiment 2	10	1	1	1
Manager Campaign	Experiment 1	1	5	1	1
	Experiment 2	1	10	1	1
Employee Campaign	Experiment 1	1	1	5	1
	Experiment 2	1	1	10	1
Market Campaign	Experiment 1	1	1	1	5
	Experiment 2	1	1	1	10
All Campaigns	Experiment 1	5	5	5	5
	Experiment 2	10	10	10	10

Table 5.7 summarises the results of all the experiments. The model predicts that if no campaigns are implemented the set target increase will be slightly higher. This is not the case for any of the other scenarios. This could be due to the fact that campaigns are focused on the stakeholder pressures which directly affect the commitment process. Overall, the higher level of intensity (multiplier 10) scenarios lead to 10% more companies committing and setting targets.

Table 5.7: Results of the first set of scenarios. The percentages presented represent the number of extra companies committing and setting target between 2020 and 2025 for each scenario. No Campaigns show the if nothing changes, the model commitment and set target outcomes will increase by 21.0% and 22.6% respectively.

Scenario	Experiment	Commitment Increase (%)	Set Target Increase %
No Campaigns	Experiment	21.0	22.6
Shareholder Campaign	Experiment 1	34.1	32.9
	Experiment 2	43.6	41.2
Manager Campaign	Experiment 1	36.0	32.6
	Experiment 2	47.1	41.9
Employee Campaign	Experiment 1	33.1	31.8
	Experiment 1	41.7	39.0
Market Campaign	Experiment 1	36.0	33.2
	Experiment 2	46.9	42.1
All Campaigns	Experiment 1	57.0	51.1
	Experiment 2	67.0	60.6

Furthermore, the most successful campaigns regarding commitment are the Manager and Market Campaigns. It is important to note that market campaign coefficient is the smallest (see Table 2.5, which is an indication that the number of connected companies become more prevalent than the market coefficients used in the equation. Regarding setting a target, the Market campaign has the highest increase of companies and Shareholder and Manager Campaign come second. The campaigns overall fair similar increases (about 35% and 45%) and their combination (All campaigns) lead to an extra 20 % increase on top of that.

Figures 5.6, 5.7, 5.8 and 5.9 present increase of committed companies and companies with targets over time. There are several interesting observations that highlight the model's characteristics. First of all, the standard deviation is significant which leads to different averages of our scenarios even before the campaigns take action. This variability makes it difficult to infer that any of the campaigns is better than the other.

Furthermore, All Campaigns and Manager Campaign commitment plots show a discontinuity around 2023. The All Campaigns scenario with a multiplier of 10 even leads an overall decrease of committed companies. This could be due to the model's predictions on failed companies (not meeting the 24-month deadline to submit their target). As time passes, and companies submit their targets, the percentage of companies that have a disadvantageous score on the scheduling and deciding dimension increases. The campaigns keep pushing these companies to commit but the companies fail to meet the deadline. The discontinuity takes place two years after the campaigns commence. It is interesting to note that, the Manager campaign which

also have this continuity at around the same time, is influenced by the Scheduling dimension thus having in common the dimension that influences the target setting process.

This set of scenarios indicate that a combination of campaigns would be much more beneficial in comparison to the existing CDP investor campaign. The model predicts a slowing down of both commitment and set target progress and this might be due to specific company characteristics that lead to a great probability of failure. In reality, what the model is indicating is that even though the past years SBTi had an exponential growth, the companies that commit tend to have characteristics that make it easier for the to submit. A change in strategy and ways to facilitate different cultures and sector characteristics could potential hasten the commitment and target setting progress.

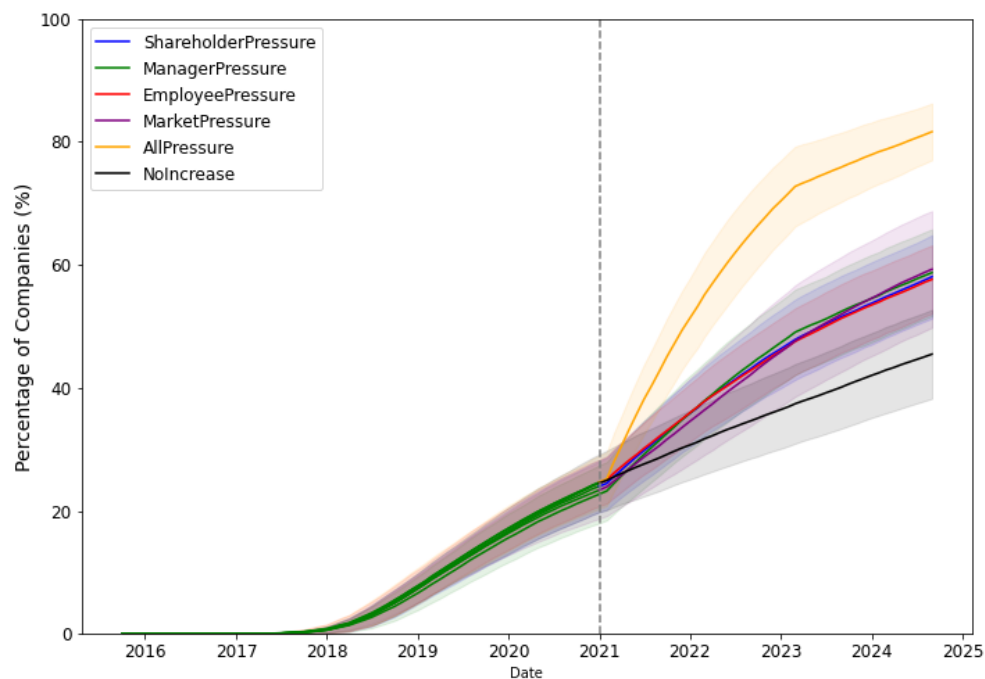


Figure 5.6: Commitments for scenarios with pressure levers set at 5

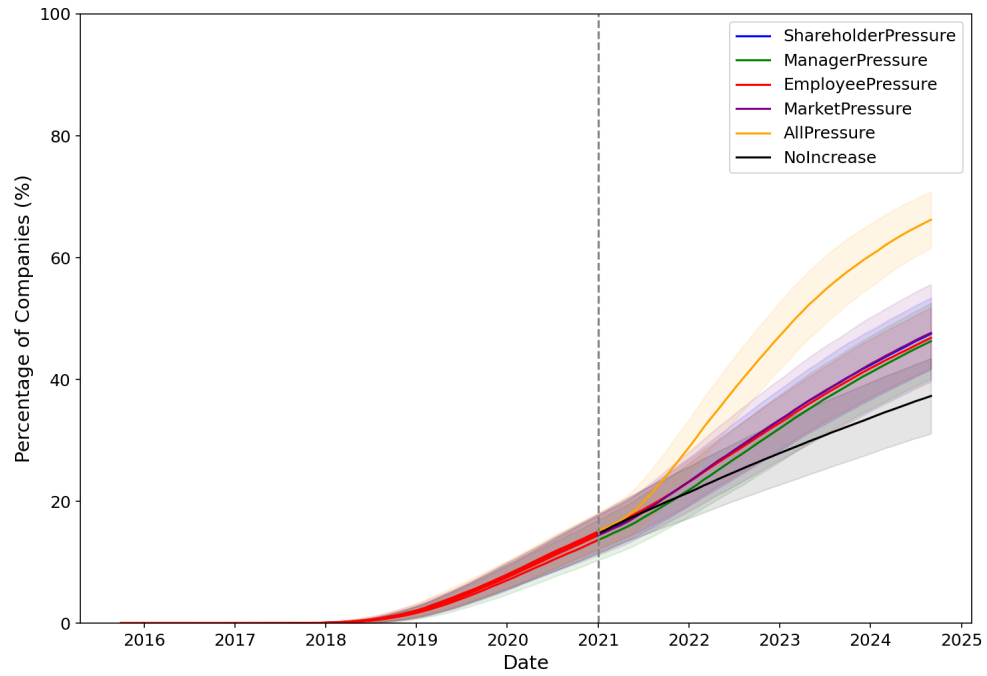


Figure 5.7: Set targets for scenarios with pressure levers set at 5

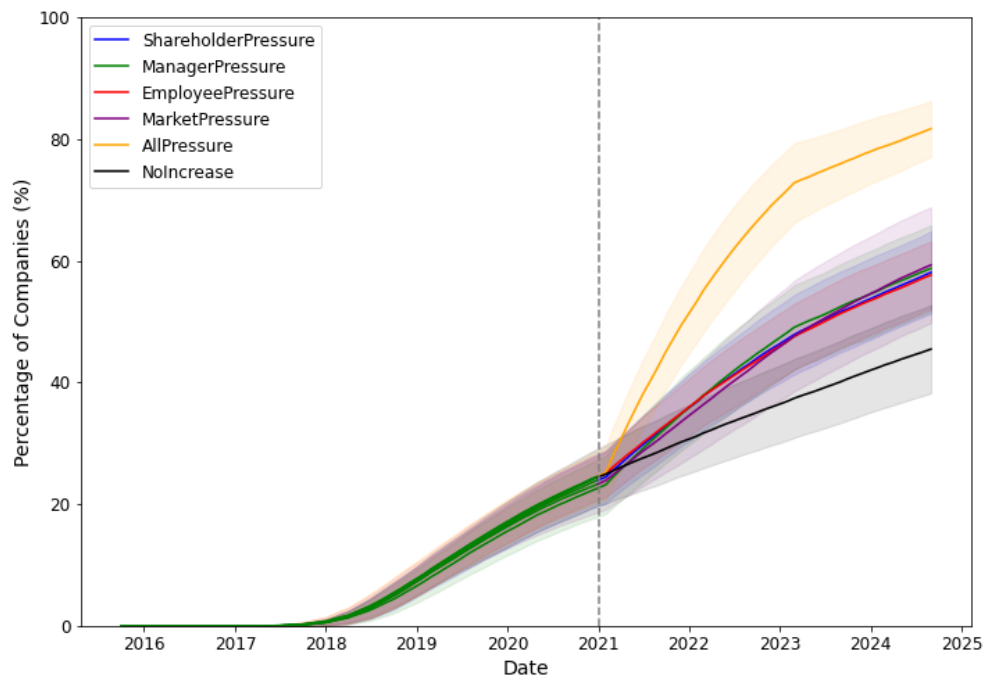


Figure 5.8: Commitments for scenarios with pressure levers set at 10

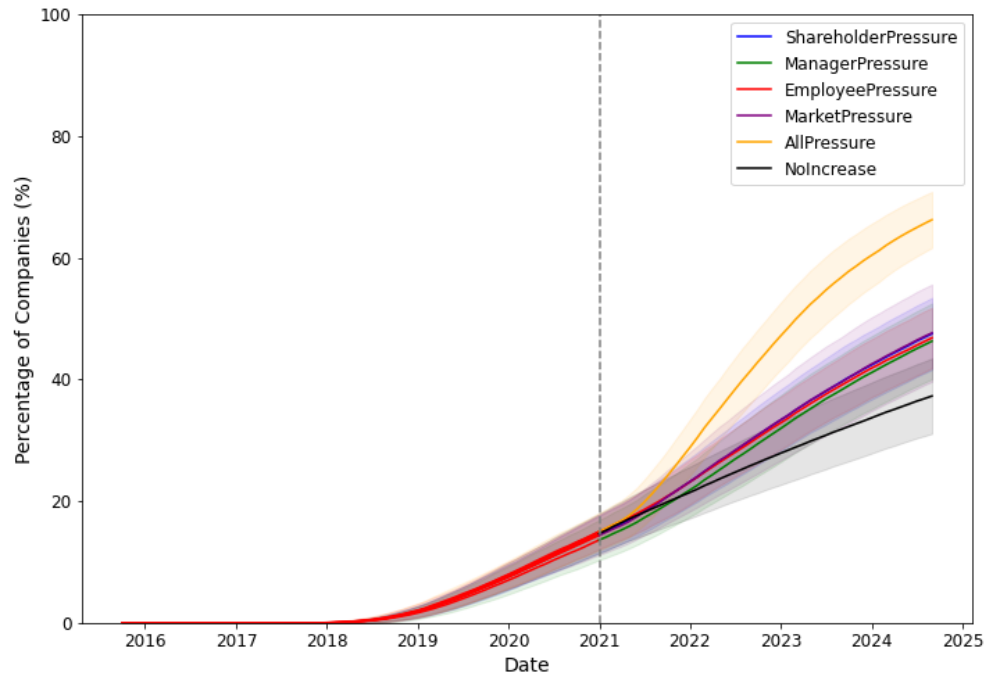


Figure 5.9: Set targets with pressure levers set at 10

The **second** set of scenarios tries to simulate campaigns and strategies based on the mechanisms already implemented on the model in an effort to create propositions as to how a campaign could lead to an increased percentage of commitments and set targets. In contrast to the simple multiplication of the pressure values of the first set, this set tries to come up with recommendations as to what the SBTi needs to do.

The first scenario is again a Market Pressure Campaign. This time the campaign is modelled differently. As previously discussed in Theoretical Underpinning, Section 2.2.4 and formalised in Conceptualisation & Formalisation, section 3.2.4, the market pressure arises from the buyers, suppliers and competitors. This translates into the connections that companies as agents make with each other. A way of simulating a campaign focusing on increasing the market pressure is to make the network more favourable for the SBTi. This was done by incorporating the following changes in the code:

- The parameter `rewiring_frequency` which represents how often a company can create a new connection with another company has been chosen to be every 13 months in the parameter tuning. This value of course is arbitrary and was chosen just so the model ends up giving similar outcomes with reality. The first change then is to increase the frequency of rewiring to take place every month. This translates to a more active action by the a
- The probability of connecting to a company that is committed is 90 % while only 10 % with companies that are not committed.

This translates to an SBTi strategy that promotes the committed companies increasing their reach as climate leaders increasing the market pressure on their connected companies. This is due to the fact that when more neighbours in the network, the market pressure increases (see equation 3.7).

The second scenario focuses on the issue of companies with specific characteristics failing to meet the 24-month deadline to set a target after they commit. A scenario where the deadline is increased to 48 months is run to test what the difference would have been if the SBTi tried to accommodate this difficulty of companies to set a target within this temporal window.

Table 5.8 presents the increase if such changes are incorporated by the SBTi. In contrast to the first set of scenarios which increases the pressures directly, these scenarios do not have a statistically significant increase on the commitments and set targets.

The new market pressure campaign which affects the network has an increase of 3 % in comparison to No campaigns at all. A closer look on the number of connections per company in the model explains the reason why. The model predicts an average of 500 connections per company. Such a large number means that the overall effect of a new connection per step even with a probability of 90 % being a committed company does not affect the pressure value of equation 3.7 significantly. This highlights the weakness of using parameter tuning for these many parameters. The explorative character of the model and its many epistemic uncertainties due to lack of knowledge (i.e. how market pressure arises and how many companies

affect a company's decision). However, it does indicate a small increase if committed companies do become promoters of the SBTi program.

The second scenario which incorporates a longer deadline from commitment to setting a target also shows a small but statistically not significant increase. As seen in the previous set of scenarios, the percentage of failing companies start becoming significant in the progress of commitment numbers at a later stage when more than 50% of companies commit. The projection to 2025 with only extending the deadline does not lead to the percentage increase seen in the previous set (see figures 5.10 and 5.11, thus the deadline parameter might not have become significant enough for the model yet).

Overall, the model show an expected increase however it is not large enough to draw any conclusive remarks from it.

Table 5.8: Results of the second set of scenarios. The percentages presented represent the number of extra companies committing and setting target between 2020 and 2025 for each scenario. No Campaigns show the if nothing changes, the model commitment and set target outcomes will increase by 21.0% and 22.6% respectively.

Scenarios	Commitment crease (%)	In- Set Target Increase (%)
No Campaigns	21.0	22.6
Market Pressure Campaign	23.95	24.88
Longer Deadline	23.89	24.72

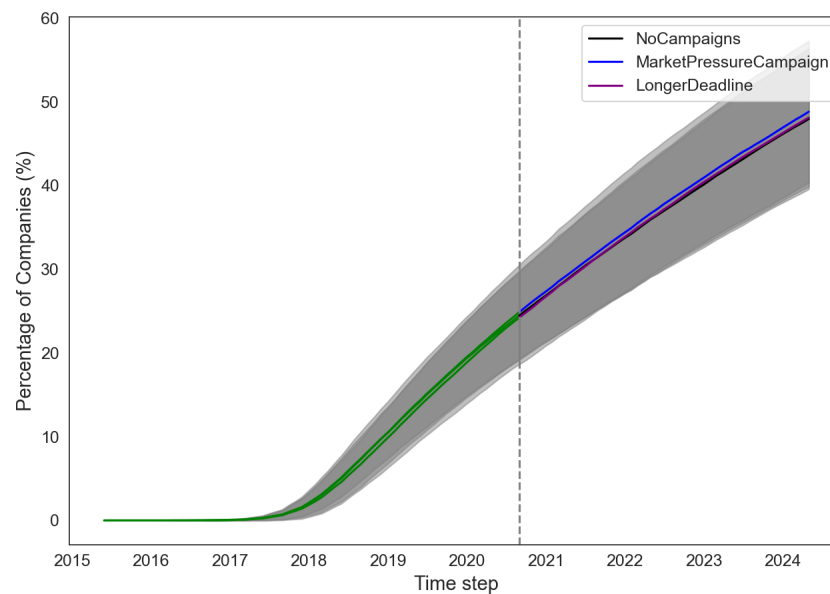


Figure 5.10: Commitments for the second set of scenarios.

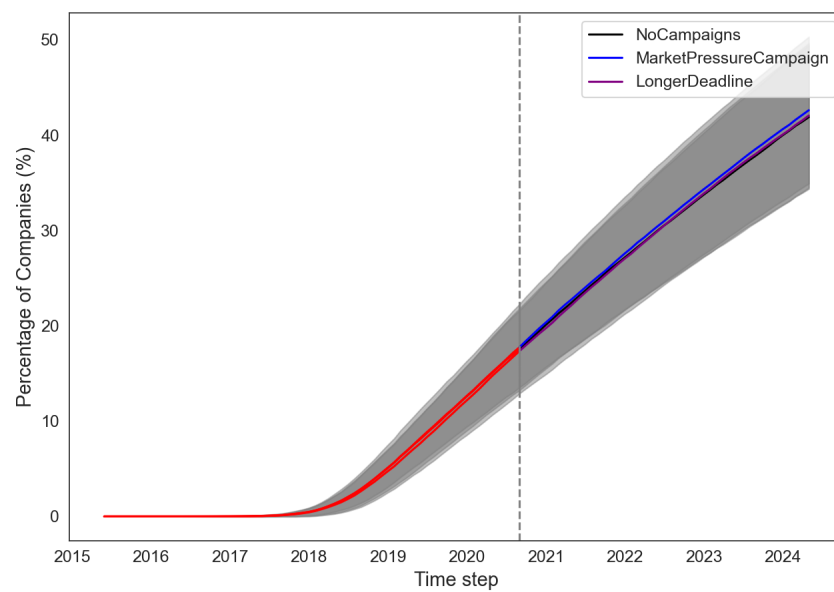


Figure 5.11: Set targets for the second set of scenarios

Chapter 6

Discussion

The SBTi has shown promise in the efforts to mitigate the global warming effects. The conclusion of this effort is to be seen, however, the exponential growth of its membership raises the question as to how normalised an SBTi commitment and target will become in the near future and how significant it can be.

The main focus of the existing literature on the SBTi and more broadly on corporate climate action focuses on the stakeholder pressures that a company faces and the corporate motivations arising from the internal conditions of a company. The research started with accumulating existing findings and combining the theoretical frameworks developed by Fink and van Hilten which tried to formulate what drives companies into SBTi. These findings were then formalised into an ABM model simulating the progress of companies from unaware to aware to finally committing and setting SBTi targets.

The model developed has tried to expand on the literature by using existing theoretical frameworks on the SBTi and country and sectoral data in an effort to find relationships between successful commitments and submissions of targets and country and sectoral characteristics. It focused on the CDP High-Impact Sample companies, a group considered the most significant stakeholders by CDP and SBTi based on their market capitalisation and emissions quantities which has become subject to focused campaigns. The scope of the simulation ends when a company submits a target to the SBTi; how it progresses with the set targets has not been included. This stage is the last of four stages a companies pass. The companies are first unaware of the SBTi, then they learn about it (aware), they then commit to set a target (committed), and finally set a target. Their dynamic development from one stage to the next is influenced by the SBTi and peer-to-peer interactions and thresholds must be surpassed before moving to the next stage (or back a stage in the case of not setting a target in a 24-month time span).

The experimentation takes place from 2015 until 2025, thus the model gets tuned on the already known commitment, target setting and average time from commitment until setting a target results, before is allowed to make short-term predictions in the future.

The analysis of the tuned model before any campaign is incorporated by the SBTi (period 2015-2020) can be broken down into two main spheres: the influence of sectoral and country characteristics.

Regarding the **sectoral characteristics**, the model results suggest that Transportation and Financial services are more successful in committing and setting a target. On the other hand, Power Generation, Manufacturing and Materials have the lowest commitments and targets. Overall, the results support the expected notion that services which are the sectors that could reduce emissions with lower costs are more flexible in setting ambitious and in our case science-based targets. On the other hand, manufacturing sectors and sectors with high emission rates find it more costly to commit to reducing their emissions. However the classification of the sectors into manufacturing, non-manufacturing and both (i.e. sectors that have both industrial aspects and services) led to a mismatch for the Food, beverages and agriculture sector.

When the model outcomes were quantitatively compared to the percentages of the high-impact companies taken from the SBTi report (2021), the Pearson r showed a weak positive correlation: 0.294 for commitments and 0.252 for set targets (when Food, beverages and agriculture sector is omitted). This indicates that while the model does capture some elements that reflect the real-world behaviour of companies in setting their climate targets, the relationship is relatively weak. These obtained values suggest that other factors not currently included in the model could influence the commitments and targets set by companies in different sectors.

The **country characteristics** were mainly the culture dimension scores taken from Erin Meyer's framework and the different number of companies per country. The culture dimensions influence several aspects of the decision-making process of companies (the assumptions are concisely summarised in Table 5.5).

The model suggests that specific cultural characteristics lead to higher percentages of commitment and set targets. For instance, countries with straightforward communication norms (lower **Communicating** scores) have higher rates of commitments and target setting. However, the model does not directly use this dimension to influence these rates but only as a similarity indication during the networking. This could point to complex interrelations between cultural dimensions or that specific countries, such as China, which has a high communicating score and low commitment and set target percentages, skew the communicating results.

The model also suggests a correlation between cultures that tend to use direct negative feedback in Evaluating actions and high commitment and set target ratio. No causation could be drawn here due to the fact that this dimension is not used in the model. Furthermore, the model suggests that cultures that tend to give more importance in trusting other stakeholders on relationships built through time and personal contact (relationship-based Trusting) are more pressured to join the SBTi. This is also true for cultures where confrontation in the case of Disagreement is acceptable.

The Deciding dimension was the only dimension that the commitment and set target percentages were higher at different sides of the spectrum. The model suggested that higher commitments were found in cultures that

favour consensus in making decisions while higher set target percentages were found in cultures that favour top-down decision making. The model's outcomes support the initial assumption that setting a target is faster for higher deciding scores even though committed companies have a lower deciding score. This could also be due to interrelations between culture dimensions or specific countries skewing the outcomes as discussed before. Finally, the Scheduling dimension analysis showed clearly that cultures that favour stricter timelines favour both commitment and set target ratios.

The strong Pearson r correlations between real data of commitment and set target for each country and model's outcomes, showcase that the hypotheses made regarding which culture dimensions while conceptualising the model, have captured at least in part the cultural trends that favour SBTi participation.

With these model trends in mind, two sets of scenarios were developed to show what strategies and campaigns would be more beneficial for the SBTi development starting in September 2020 and ending in September 2025.

The first set of scenarios tests what would happen to the commitment and set target progress if the shareholder, manager, employee and market pressures are increased by a factor of 5 and 10. These were arbitrary values that pressed more companies to pass the threshold for commitment.

The scenario of the increased Market Pressure, which is the pressure coming from the network of other companies surrounding a company in question, such as supply chain firms, competitors, buyers etc. topped the commitment and set target percentages. The second most significant commitment increase came from the Manager pressure Campaigns, which would be campaigns focused on supporting management in putting more effort in allocating a higher budget to climate action. The Shareholder pressure campaigns scored lower regarding commitment increases but led to similar percentages of set targets with the Manager Campaigns. The employee pressure campaigns have the lowest but still significant increase (12.1% and 9.2% more committed companies and companies with targets respectively). A combination of all the campaigns does lead to a larger increase however it does show to be limited by specific dynamics present in the model. Some companies with unfavourable culture and sectoral characteristics cannot pass the commitment threshold or if they do pass they don't meet the deadline to set a target due to a combination of flexible scheduling score and consensual deciding which slow down the decision process.

The second set focuses on how SBTi could increase its commitment either by increasing pressures or by changing its strategies, based on the model mechanisms. The first scenario explores a situation in which the SBTi creates the conditions for its members to become climate leaders increasing their reach and connections. The second scenario checks how much a longer deadline for a committed company to set a target would affect the percentage increase of the committed and set targets. These two scenarios show a slight increase but are not statistically significant. Thus, conclusive significant strategy recommendations can be drawn from the model's mechanism.

In conclusion, the results have highlighted a significant influence based on the cultural dimensions and there were indications showing that the company's sector also plays a role in joining the SBTi. The scenarios offered some insights as to which campaigns could be more beneficial. The model predicts that market pressure campaigns and manager campaigns fare better than the already existing shareholder CHIS campaign. The limitations of the model are discussed in the final chapter, the Conclusion.

Chapter 7

Conclusions

The final chapter starts by revisiting the research questions that were proposed in relation to the development of the SBTi and how well they were answered with the described methodology (Section 7.1). The next section reflects on the limitations of the research approach (Section 7.2). The scientific contributions are then discussed (section 7.3). Finally, future research paths (Section 7.4) and recommendations to the SBTi are proposed (Section 7.5).

7.1 Conclusions

The thesis focused on the recently established and rapidly growing SBTi, an international initiative that strives to hasten the climate action by providing guidelines and analysing the set targets and how they relate to the science-based knowledge existing at the moment.

The literature has highlighted some promise into the whole initiative but more is to be seen in the next years. Several theses, most notably van Hilten, [2022](#) and Fink, [2018](#), have made efforts in understanding what drives the companies to join the specific initiative. The focus surrounded corporate motivations and pressures. The goal of this thesis was to provide indications as to how the different motivations and pressures relate and what characteristics of companies have highest probability in committing and setting targets to the SBTi. Furthermore, suggestions as to what strategies could increase the uptake of the SBTi which would potentially increase its effectiveness.

The complexity of interactions and the multitude of factors that affect the decision-making of companies led to the choice of ABM as the research approach to answer the main research question "*Why do companies join the SBTi?*".

To answer the main research question, the thesis is structured in answering the following sub-questions (referred to as RQ. X from here onwards). The first four were answered in the Theoretical Underpinning Chapter 2 while the final two were the focus of the ABM experimentation.

1. What are the existing strategies and campaigns of SBTi to incentivize high-impact companies to commit and set science-based targets?
2. What are the current motivations for companies to join climate action according to previous research?
3. What are the current stakeholder pressures that incentivize climate action according to previous research?
4. What are the factors that have been identified as related to companies joining SBTi from existing research?
5. How does the combination of these factors (questions above) affect the uptake of companies?
6. What are potential strategies that SBTi can implement to speed its uptake?

Starting with **RQ.1**, the thesis delves into understanding how the SBTi leads campaigns in attracting new members. Since 2020, a large-scale campaign focusing on a group of high-impact companies which was selected by the CDP (one of the founding organisations for the SBTi) commenced. It is now running its third year and has mostly focused on increasing the investor(shareholder) pressure by contacting Financial institutions to support the cause and place pressure on the companies that have not yet committed and are part of the the high-impact group. The analyses of the CDP (CDP, 2021) and (CDP, 2022), have shown that many of the high-impact companies ended up joining since the initiations of the campaigns. Even though the impact of the campaign cannot be conclusive, since other parameters play a role such as regulatory, market, employee and manager pressures or even individual motivations which are dynamic and change with time, there was exponential growth in both commitments and targets set by high-impact companies since 2020 which is an indication that the campaign does help the uptake of the SBTi.

The **RQ.2** was mainly a literature review focusing on the existing findings regarding corporate climate action and more specifically on the SBTi. The main inputs came from the master theses of van Hilten 2022 and Fink 2018, which used two different theoretical frameworks to test various categories of motivations.

According to both van Hilten and Fink, legitimacy plays a crucial role to join the SBTi. Van Hilten's qualitative interview-based research and quantitative research indicated that companies joining the SBTi are motivated because they want to have a good reputation among business competitors, suppliers and buyers. The interviews made with the companies also indicated that the end consumers exert less influence on companies' decisions to join SBTi. This is consistent with Fink's findings that climate reputation is not chiefly focused on consumers but more on corporate stakeholders.

Van Hilten also found that larger companies and those with intangible assets, indicating innovativeness, are more likely to join SBTi, which supports that companies driven for market success and growth are more motivated to join the SBTi. Fink identified similar trends under the concept of climate leadership. Companies that strive climate leadership to improve their market position, view SBTi as a platform that can facilitate this goal.

Van Hilten's third motivation category was Social Insurance. The interviews made during her work suggested companies find the risks that are connected to climate change highly important which is a driver for them to join the SBTi to mitigate those risks. Fink's "climate risks" category, which includes regulatory, physical, and market risks, complements this point although she found that companies don't primarily see SBTi as a tool for risk mitigation. Van Hilten also evaluated the organizational culture and found that board, gender and culture diversity correlate with the decision to join the SBTi.

Another interesting outcome from Van Hilten's study showed that the desire for internal improvement was the least motivating factor for companies to join SBTi, casting doubt on companies perceive SBTi as an organization that can provide companies with the technical knowledge and the support they require. This notion was supported by Fink's interviews which indicated that companies are skeptical about SBTi's role in mitigating climate risks, a category which could be related to internal improvements.

Fink further explored how the organizational attributes of SBTi itself could influence companies to join. Companies were generally satisfied with the quality of information provided by SBTi, but this wasn't a major factor in their decision to join. The informal monitoring by SBTi was seen as less effective, and the benefits it offered were not viewed as highly significant.

In **RQ.3** the focus was shifted into pressures rather than motivations. Even though, the two are interrelated, the model makes an effort in making a distinction between motivation internal to the agent's decision making and pressures coming from the stakeholders. This is a theoretical limitation and will be discussed in the next section. RQ.3 was also a literature-based question that explored what kinds of pressures lead to climate action. Even though, the concept of pressures was not explicitly explored for the SBTi, the literature review led to some broad patterns, that were more succinctly summarised in the recent meta-analysis by Wang et al., 2020. According to this report, the most significant pressures regarding climate actions arise from internal pressures such as shareholders, managers and employees, followed by regulatory pressures, market pressures and lastly social pressures (NGOs, public). The first three pressures scored similarly while social pressure category deemed not significant.

To answer **RQ 4** factors beyond pressures and motivations that influence SBTi commitment and setting a target were found in literature. Previous studies have shown that companies with internal targets move to setting an SBTi target faster than companies with no internal emission reduction targets. Furthermore, companies in sectors with a higher fraction of committed firms are more likely to commit themselves, suggesting a kind of 'peer pressure' within sectors (Freiberg et al., 2021).

Coercive pressure from national policy also has shown to play a role. Companies in countries with intended nationally determined contributions (INDCs) are more likely to commit to SBTi. Interestingly, this commitment goes down when these countries transition from INDCs to nationally determined contributions

(NDCs), possibly because companies perceive that the government has assumed responsibility for emissions reductions (Bolton & Kacperczyk, 2022).

Another noteworthy factor is the carbon intensity of the sector to which a company belongs. Companies from higher carbon-intensive sectors are less likely to make commitments to SBTi. Similarly, firms from low- and middle-income countries are less likely to commit to SBTi targets (Bjørn et al., 2022).

Thus RQ.4 identified sectoral trends, national policies, prior internal targets, and the location-specific trends within which a company operates.

The final two research questions were answered during the experimentation step of the ABM modelling. **RQ.5** provides insights on what company characteristics are more beneficial in joining the SBTi. The main findings can be divided into two groups and vary in statistical confidence.

Firstly, the sectoral characteristics indicated that non-manufacturing companies clearly commit and set targets more than manufacturing type companies. The real data even though agrees with the general trends also suggests that there are more things at play that the model cannot capture, with sectors such as Materials (manufacturing type) having a high percentage of commitments and set targets.

The second group was the based on the country of origin. The model did predict with a high statistical confidence the percentages of commitments and set targets per country. The country of origin was used to relate culture dimension scores from Erin Meyer's culture mapping tool to the companies. There were inferences drawn regarding what kind of cultures are more likely to commit or set targets. Specifically, companies from countries characterized by straightforward communication norms, a willingness to directly evaluate negatively, a tendency to confront in cases of disagreement, trust based on personal contact, a preference for strict deadlines, and a more egalitarian power structure were found to be more likely to commit or set targets. However, the deciding factor presented a complex picture: companies from cultures that prioritize consensus were more inclined to commit, whereas those from top-down cultures were more likely to actually set a target, perhaps because their decision-making processes did not require universal agreement which can be time consuming.

For **RQ.6**, several scenarios were implemented up to 2025 to test how specific campaigns would influence the uptake of the SBTi. It has been shown that model predicts higher commitment and set targets rates when Market and Manager pressures are increased. The shareholder pressure campaign fare better regarding setting targets than committing. What the model clearly showed though is how a combination of campaigns leads to a very rapid increase for the uptake of the SBTi. In an effort, for test specific strategies two extra scenarios were run: an increase in networking and reach of the committed companies in their sector and location and a longer deadline. Both of them showed a slight increase in commitment and targets however no conclusive outcomes could be drawn from such an increase.

Going back to the main research question as to "Why companies join the SBTi", it became clear that the complexity of the dynamics that affect the uptake of the SBTi meant that the model could not completely answer it. The limitations on data and the epistemic uncertainty of concepts such as pressure and motivation led to a bigger focus on the cultural and sectoral dimension. The model managed to provide insights regarding the importance of cultural dimensions opening a path into a potential further research on how the SBTi could consider the specificities on different cultures to maximize its effect.

7.2 Research Limitations

It is to be expected that such a model with a prognostic character will have a variety of limitations. These limitations can be divided into three main groups: data-based, conceptual and technical.

The **data limitations** arise from the lack of a freely-available database for data regarding the high-impact companies. The model was built based mainly on the SBTi Report numbers of commitments and set targets of high-impact companies for different countries and sectors and the types of sectors. There was no data available on which countries failed to meet the 24-month deadline. Furthermore, emissions and types of sectors had to pass through an elaborate process discussed in Appendix A.2 before they were used, with the percentage emissions per sectors being extrapolated just from CDP Europe which might not be representative in the global scale.

An interesting approach was used by van Hilten [2022](#) who in her thesis translated the corporate motivation categories of legitimacy, market success, social insurance, organisational culture and internal improvement into tangible characteristics. For instance, the presence of risk committee was considered a prefix that indicates social insurance and the intangible assets of a company was one of the prefixes used to indicate market success. However, her scope was the Fortune 500 companies from 2015 to 2021 (6 years) and in her statistical analysis, she tried to gather 3000 observations (500 companies for 6 years). The outcome of this data collection was that only 805 complete observations were found and only from 135 companies. A more complete dataset using these prefixes could have been used instead of the pressure weights taken from Wang et al., [2020](#) which are not focused specifically on SBTi. To compensate with the lack of data that could be used to signal motivation categories, the culture dimensions were used instead, which is a method that has not specifically studied for corporate climate action.

The second group, the **conceptual limitations**, is strongly related to the lack of data. Many assumptions were made in the process of formalising the model. These conceptual limitations will be broken into the four main model process: network, awareness, commitment and set target.

The network of connections between companies was based on 3 main parameters: country identity, sector identity and communicating dimension similarity (i.e. how similar their communication style is). There are several weaknesses in such an approach. First of all, many other parameters that could lead to companies

being connected were not included: such connections due to a company supplying or buy from another. There was an effort by incorporating an extra weight on these factors, however it still remains that the network was not strongly backed by any literature. Another main assumption for the network is that the model simulates a closed system where only high-impact companies interact, inform and put pressure to each other. However, high-impact companies interact with smaller suppliers, buyers or companies that didn't make it in the CDP list.

The awareness process was included in order to take into consideration the fact that a new initiative like SBTi needs time to be known by the companies. The sensitivity analysis has shown that the model is very sensitive to the parameters influencing awareness which indicates that the awareness process is the main driver for the final number of companies committing or setting a target. The awareness process, after the parameters are set to match the desired outcomes of 2020, becomes irrelevant when experimentation starts since all companies in the model become aware. A more elaborate approach would be needed to understand what it means to be aware the SBTi. It could mean either just know about it or really considering joining. It should also be noted that the model spread of awareness does not take into the geographic or sectoral specificities of SBTi campaigns but happens randomly. This is something that could have been included in the model.

In the commitment process, the conceptual limitations regarding motivation and pressure become apparent. During the conceptualisation this two concepts were treated as distinct categories. However, there are weaknesses in such as assumption since many of them overlap. For instance, market pressure and market success do rely on other companies. The model's structure distinguishes the two by giving an random intrinsic value of market success to the company (i.e. an individual random value to describe its intrinsic character) and the market pressure is influenced by its neighbours.

The culture dimensions choices in the model were made by the author in a "what-if" manner. There was no systematic approach to the choice nor previous literature to base the choices made. A more coherent approach made by an expert could have provided more insights regarding the effects of culture on climate action. This being said, it is interesting that the assumptions have led to some very insightful outcomes regarding the cultures that lead to more commitments and targets which are backed by the existing data on the percentages of companies joining the SBTi per country.

The target setting process was also based on limited data on how long companies need to set a target with extensive estimations made in order to get an estimated value (further elaboration in Appendix A.4). This data limitation meant that there was no indication if the process described matches reality. Interestingly enough, set target percentages per country did correlate strongly with the model's outcomes, thus scheduling and deciding cultures could be playing a crucial role.

Finally, there were **technical and practical limitations**. Running the model once with 2233 agents was taking approximately 15 minutes (also dependent on the number of steps). It is common practice to run

each experiment 100 times. This however, would have meant 25 hours for each scenario. Even with the multiprocessing library, this was very computational intensive and time consuming, thus compromises were made during sensitivity analysis, parameter tuning and experimentation. This also led to concessions on increasing the complexity of the model further for the present thesis.

In conclusion, the model has a prognostic character. In other words, it is a model that is trying understand the laws that influence the behaviour of the corporate climate action arena. For instance, there is significant epistemic uncertainty not only in understanding the concepts of motivations and pressures but even more so in attempting to model them (Saltelli et al., 2007). However, having all this in mind, the model did lead to some useful insights.

7.3 Scientific Contribution

The scientific contributions of this research are manifold and interconnected, setting new precedents in several areas. First, this study is the first to employ Agent-Based Modeling (ABM) as a method to simulate the uptake of the SBTi. Although ABM in the context of climate action is a relatively new methodological approach, it has shown promise for enhancing our understanding of private governance in climate-related matters. While the ambitious objective of definitively explaining why companies opt to join the SBTi remained somewhat elusive, the study does offer interesting insights into the dynamics of corporate interactions and peer pressures related to this commitment.

Furthermore, the integration of theoretical frameworks focused on motivations and pressures in a single model represents an innovative approach. It could possibly provide a fresh perspective but also be used for future research on how such complex social constructs can be meaningfully modeled.

Additionally, the application of Erin Meyer's Culture Map to attribute characteristics to companies in relation to their climate action initiatives was not used before. The framework has mainly been used to explain behaviours within a company and not to explain the behaviour of a company as a whole. This unique incorporation adds a new layer of understanding to the cultural factors influencing corporate behavior in climate governance.

7.4 Future research

In terms of future research, several paths could be developed further to enrich the applicability of such a model. One immediate improvement would be to enrich the model with more comprehensive and systematically gathered data on motivations and pressures related to climate action. This could be done on proxy characteristics, examples of which can be found in van Hilten's thesis 2022.

Furthermore the selected cultural dimensions and their influence on the commitment and set targets can be validated through expert evaluation. Such validation would lend greater credibility and generalizability to the findings, making them more actionable and transferrable to similar modelling explorations.

As discussed before, the model's focus ends when companies set a target. Future models could benefit from simulating the post-submission phase. This would offer a more comprehensive view on the importance of the SBTi in climate action. Furthermore, the rapidly growing initiative could rapidly reach very high percentages of commitments and targets thus a model limited to pre-submission simulation can become outdated in the near future. This would be due to the fact that setting targets would become secondary as the importance would shift to actually reducing the emissions according to those targets.

Moreover, integrating different methodologies, like statistical analysis, alongside the existing Agent-Based Modeling (ABM) framework, could provide a more rounded understanding of the factors that influence corporate commitments to climate action.

7.5 Recommendations to SBTi

Based on the model's findings, two recommendations emerge that could substantially inform the SBTi's strategy going forward. the first recommendation is that focusing solely on shareholder pressure via the SBTi-CDP High-impact Company campaigns may be narrowing the initiative's efficacy. Instead of concentrating exclusively on shareholders, the SBTi might consider a more encompassing approach for stakeholder engagement. This could be done by actively involving other stakeholders of a company's environment such as management, employees, and peer organizations in their campaigns. The SBTi could thus accelerate the pace at which companies commit and set targets.

The second recommendation, arises from the model's findings on the role of culture in decision-making related to climate action. By considering a company's country of origin the SBTi could tailor its engagement strategies to suit varying cultural norms.

Bibliography

- Andersen, I., Ishii, N., Brooks, T., Cummis, C., Fonseca, G., Hillers, A., Macfarlane, N., Nakicenovic, N., Moss, K., Rockström, J., Steer, A., Waughray, D., & Zimm, C. (2020). Defining “science-based targets”. *National Science Review*, 8. <https://doi.org/10.1093/nsr/nwaa186>
- Bakhtiari, F. (2018). International cooperative initiatives and the united nations framework convention on climate change [Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/14693062.2017.1321522>]. *Climate Policy*, 18(5), 655–663. <https://doi.org/10.1080/14693062.2017.1321522>
- Banda, M. L. (2018, January 16). The bottom-up alternative: The mitigation potential of private climate governance after the paris agreement. Retrieved November 2, 2022, from <https://papers.ssrn.com/abstract=3134197>
- Bertotti, M. L., & Modanese, G. (2019). The configuration model for barabasi-albert networks [Number: 1 Publisher: SpringerOpen]. *Applied Network Science*, 4(1), 1–13. <https://doi.org/10.1007/s41109-019-0152-1>
- Bjørn, A., Tilsted, J. P., Addas, A., & Lloyd, S. M. (2022). Can science-based targets make the private sector paris-aligned? a review of the emerging evidence. *Current Climate Change Reports*, 8(2), 53–69. <https://doi.org/10.1007/s40641-022-00182-w>
- Bolton, P., & Kacperczyk, M. T. (2022, June 7). Firm commitments. <https://doi.org/10.2139/ssrn.3840813>
- Borrás, S., & Edler, J. (2014, January 1). The governance of change in socio-technical and innovation systems: Three pillars for a conceptual framework. <https://doi.org/10.4337/9781784710194.00011>
- Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, 77(1), 34–49. <https://doi.org/10.1016/j.techfore.2009.08.002>
- Calder, M., Craig, C., Culley, D., de Cani, R., Donnelly, C. A., Douglas, R., Edmonds, B., Gascoigne, J., Gilbert, N., Hargrove, C., Hinds, D., Lane, D. C., Mitchell, D., Pavey, G., Robertson, D., Rosewell, B., Sherwin, S., Walport, M., & Wilson, A. (2018). Computational modelling for decision-making: Where, why, what, who and how [Publisher: Royal Society]. *Royal Society Open Science*, 5(6), 172096. <https://doi.org/10.1098/rsos.172096>

- Cashore, B., Auld, G., & Newsom, D. (2004). *Governing through markets: Forest certification and the emergence of non-state authority*. Yale University Press. Retrieved November 11, 2022, from <https://www.jstor.org/stable/j.ctt1npqtr>
- CDP. (n.d.). *The CDP climate high-impact sample (CHIS) explained*. https://cdn.cdp.net/cdp-production/comfy/cms/files/files/000/003/668/original/CDP_SBT_Campaign_High-impact__sample_explained.pdf.
- CDP. (2021). *CDP science-based targets campaign- final progress report: 2020 campaign*.
- CDP. (2022). *CDP science-based targets campaign- final progress report: 2021-22 campaign*.
- CDP Worldwide. (2022). *CDP's activity classification system (CDP-ACS)*.
- Choo, C. W. (1996). The knowing organization: How organizations use information to construct meaning, create knowledge and make decisions. *International Journal of Information Management*, 16(5), 329–340. [https://doi.org/10.1016/0268-4012\(96\)00020-5](https://doi.org/10.1016/0268-4012(96)00020-5)
- Eslamizadeh, S., Ghorbani, A., Costa, R. C. B. F., Künneke, R., & Weijnen, M. (2022). Industrial community energy systems: Simulating the role of financial incentives and societal attributes. *Frontiers in Environmental Science*, 10. Retrieved November 11, 2022, from <https://www.frontiersin.org/articles/10.3389/fenvs.2022.924509>
- Fink, L. O. (2018, May). *What drives firms to successfully cooperate on climate change? - an institutional analysis of the science based targets initiative* (Doctoral dissertation). Humboldt-Universität Berlin.
- Freiberg, D., Grewal, J., & Serafeim, G. (2021, March 28). Science-based carbon emissions targets. <https://doi.org/10.2139/ssrn.3804530>
- Hadjimichael, A. (2020, March 23). *Determining the appropriate number of samples for a sensitivity analysis – water programming: A collaborative research blog*. Retrieved July 13, 2023, from <https://waterprogramming.wordpress.com/2020/03/23/determining-the-appropriate-number-of-samples-for-a-sensitivity-analysis/>
- Hsu, A. (2016). Track climate pledges of cities and companies.
- Initiative, S. B. T. (2015). *Sectoral decarbonisation (SDA): A method for setting corporate emission reduction targets in line with climate science- version 1*.
- IPCC. (2023). *SYNTHESIS REPORT OF THE IPCC SIXTH ASSESSMENT REPORT (AR6)*.
- Kaaronen, R. O., & Strelkovskii, N. (2020). Cultural evolution of sustainable behaviors: Pro-environmental tipping points in an agent-based model. *One Earth*, 2(1), 85–97. <https://doi.org/10.1016/j.oneear.2020.01.003>
- Kuo, L., & Chang, B.-G. (2021). Ambitious corporate climate action: Impacts of science-based target and internal carbon pricing on carbon management reputation-evidence from japan. *Sustainable Production and Consumption*, 27, 1830–1840. <https://doi.org/10.1016/j.spc.2021.04.025>
- Kuramochi, T., Roelfsema, M., Hsu, A., Lui, S., Weinfurter, A., Chan, S., Hale, T., Clapper, A., Chang, A., & Höhne, N. (2020). Beyond national climate action: The impact of region, city, and busi-

- ness commitments on global greenhouse gas emissions [Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/14693062.2020.1740150>]. *Climate Policy*, 20(3), 275–291. <https://doi.org/10.1080/14693062.2020.1740150>
- Kwakkel, J. (2023). *EMA workbench documentation-release: 2.5*. <https://emaworkbench.readthedocs.io/en/latest/index.html>
- Lerner, M., & Osgood, I. (2022). Across the boards: Explaining firm support for climate policy [Publisher: Cambridge University Press]. *British Journal of Political Science*, 1–24. <https://doi.org/10.1017/S0007123422000497>
- Lui, S., Kuramochi, T., Smit, S., Roelfsema, M., Hsu, A., Weinfurter, A., Chan, S., Hale, T., Fekete, H., Lütkehermöller, K., Jose de Villafranca Casas, M., Nascimento, L., Sterl, S., & Höhne, N. (2021). Correcting course: The emission reduction potential of international cooperative initiatives [Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/14693062.2020.1806021>]. *Climate Policy*, 21(2), 232–250. <https://doi.org/10.1080/14693062.2020.1806021>
- Meyer, E. (n.d.). *The country mapping tool*. Retrieved June 18, 2023, from <https://erinmeyer.com/tools/culture-map-premium/>
- Meyer, E. (2014). *The culture map: Breaking through the invisible boundaries of global business*. PublicAffairs.
- Nikolic, I., & Ghorbani, A. (2011). A method for developing agent-based models of socio-technical systems. *2011 International Conference on Networking, Sensing and Control*, 44–49. <https://doi.org/10.1109/ICNSC.2011.5874914>
- Oliver Wyman. (2021, March). *Running hot- accelerating europe’s path to paris*. CDP. https://cdn.cdp.net/cdp-production/cms/reports/documents/000/005/578/original/Running_hot_-_accelerating_Europe’s_path_to_Paris.pdf?1615190423
- Paris Agreement (2016). Retrieved December 6, 2022, from [https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:22016A1019\(01\)](https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:22016A1019(01))
- Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., & Tarantola, S. (2007). Introduction to sensitivity analysis [Section: 1 _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/9780470725184.ch1>]. In *Global sensitivity analysis. the primer* (pp. 1–51). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9780470725184.ch1>
- SBTi. (n.d.-a). *How to set a science-based target - a step by step guide* [Science based targets]. Retrieved March 13, 2023, from <https://sciencebasedtargets.org/step-by-step-process>
- SBTi. (n.d.-b). *SBTi progress report 2021* [Science based targets]. Retrieved July 3, 2023, from <https://sciencebasedtargets.org/reports/sbti-progress-report-2021>
- SBTi. (2015, May). *Campaign launches to close the gap between corporate GHG reduction goals and a 2°C scenario* [Science based targets]. Retrieved June 19, 2023, from <https://sciencebasedtargets.org/news/campaign-launches-to-close-the-gap-between-corporate-ghg-reduction-goals-and-a-2-c-scenario>

- SBTi. (2022, June). *Scaling urgent corporate climate action worldwide- science- based targets initiative annual progress report, 2021*. <https://sciencebasedtargets.org/resources/files/SBTiProgressReport2021.pdf>
- Science Based Targets initiative. (2021). *SCIENCE-BASED NET-ZERO scaling urgent corporate climate action worldwide*.
- Simões-Coelho, M. F., & Figueira, A. R. (2021). Why do companies engage in sustainability? propositions and a framework of motivations. *BAR - Brazilian Administration Review*, 18(2), e190042. <https://doi.org/10.1590/1807-7692bar2021190042>
- Spencer Stuart. (2022, March). *Board governance: International comparison chart*. Retrieved June 19, 2023, from <https://www.spencerstuart.com/research-and-insight/international-comparison-chart>
- ten Broeke, G., van Voorn, G., & Ligtenberg, A. (2016). Which sensitivity analysis method should i use for my agent-based model? *Journal of Artificial Societies and Social Simulation*, 19(1), 5.
- UNEP. (2018). Emissions Gap Report 2018 [Section: publications]. *United Nations Environment Programme*. Retrieved November 11, 2022, from <http://www.unep.org/resources/emissions-gap-report-2018>
- United Nations Framework Convention on Climate Change. (n.d.). *About the secretariat*. Retrieved December 6, 2022, from <https://unfccc.int/about-us/about-the-secretariat>
- United Nations Framework Convention on Climate Change. (2022). *Climate plans remain insufficient: More ambitious action needed now* | UNFCCC. Retrieved December 6, 2022, from <https://unfccc.int/news/climate-plans-remain-insufficient-more-ambitious-action-needed-now>
- Vandenbergh, M. (2013). Private environmental governance. *Cornell Law Review*, 99.
- van Hilten, E. (2022, August). *Why corporates join the science based targets initiative- a mixed-method study on the fortune 500* (Doctoral dissertation). Delft University of Technology.
- Wang, L., Li, W., & Qi, L. (2020). Stakeholder pressures and corporate environmental strategies: A meta-analysis [Number: 3 Publisher: Multidisciplinary Digital Publishing Institute]. *Sustainability*, 12(3), 1172. <https://doi.org/10.3390/su12031172>
- White, R. (1994). Preface. in b. r. allenby & d. j. richards (eds.), *the greening of industrial ecosystems* (B. R. Allenby & D. J. Richards, Eds.). The National Academies Press. <https://doi.org/10.17226/2129>
- Widerberg, O., & Pattberg, P. (2015). International cooperative initiatives in global climate governance: Raising the ambition level or delegitimizing the UNFCCC? [eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/1758-5899.12184>]. *Global Policy*, 6(1), 45–56. <https://doi.org/10.1111/1758-5899.12184>
- Windolph, S. E., Harms, D., & Schaltegger, S. (2014). Motivations for corporate sustainability management: Contrasting survey results and implementation [eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/csr.1337>]. *Corporate Social Responsibility and Environmental Management*, 21(5), 272–285. <https://doi.org/10.1002/csr.1337>

Appendix A

Appendix

A.1 Estimation of companies that are committed or have a target for 2020

The number of high-impact companies that have already committed or set a target is provided in SBTi Progress Report. However, the number reflects the year 2021, which is a year after the first CDP high-impact campaign (see Section 2.1.3). The decision was to calibrate the model to reality before the campaigns are run i.e. 2015- 2020. Thus, the 2020-2021 campaign success number (CDP, [2021](#)) is subtracted from the reported numbers of the SBTi Progress Report 2021. The table below summarises the calculation the percentage of Committed+Setting Target (in the model companies that set target stay in the committed number) and Setting Target. For further information on the calculations, see in Supplementary Materials, the excel file StructureData.xlsx, worksheet "High-impact comm-targets% 2020".

Table A.1: Targets and Commitments in 2020

Year	Not committed	Committed	Set Target	Total	Reference
2021	1635	290	308	2233	Science Based Targets initiative, 2021
154 companies committed or set target between September 2020 and August 2021					
CDP Campaign 2020-2021	NaN	123	31	154	CDP, 2021
Subtracting the two gives us the number in 2020					
2020	1789	167	277	2233	
In the model, companies that set a target are also counted as committed: 444 (Committed + Set Target), 277 (Set Target)					
Percentage: 19.88% (Committed), 12.40% (Set Target)					

A.2 Emission distribution

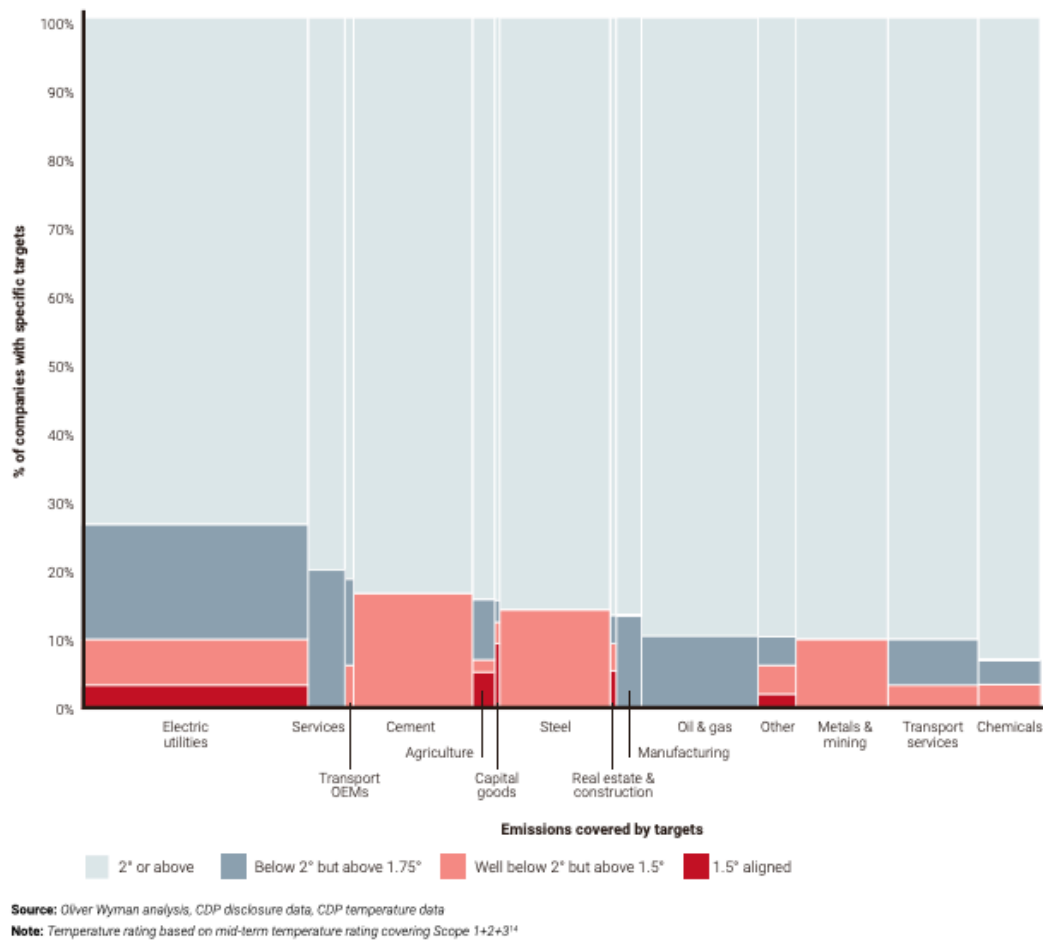


Figure A.1: Annual cumulative number of companies with approved targets and commitments between 2015–2021. Taken from (Oliver Wyman, 2021, p. 10). The values used are taken from the interactive infographic of the website.

The SBTi Progress report (Science Based Targets initiative, 2021) divides the CDP high-impact companies into 13 sectors (see figure 2.3. This division was based on the CDP’s Activity Classification System (CDP-ACS) which is a framework used to categorize companies to the most relevant sectors for the CDP surveys (CDP Worldwide, 2022). The classification of companies to specific sectors varies from organization to organization. In order to allocate emissions to each sector, the distribution of emissions to sectors made by Oliver Wyman consulting firm in collaboration with CDP for the companies that are members of CDP in Europe is used. It has to be noted that this assumption neglects any variation between different continents or between samples of companies, since the distribution is then extrapolated worldwide and even more specifically to the high-impact companies group.

The percentage of emissions per sector is taken from figure A.1. The sectors represented in this analysis don't completely align with the sectors used by SBTi to classify companies so further assumptions are taken aligning the sectors of figure 2.3 to the sectors of figure A.1 (see Table A.2 and the Supplementary Materials, in the excel file StructureData.xlsx, worksheets "SBTiProgressReport_Sectors", "CDPEurope Report_Sectors" and "SectorAlignment"). The total emissions of the high impact companies is estimated to be 13.5 Gt (Oliver Wyman, 2021, p. 26).

The sector type (Manufacturing/Non-manufacturing) was a distinction needed to assign different weights of stakeholder pressure to the companies. The sectors were allocated to each of the two categories based on their main activity. The service sectors (transport service, financial services) clearly provide services while food, beverages and agriculture, power generation, manufacturing and materials generate a physical product. Infrastructure sector and Other were placed as having both manufacturing and non-manufacturing functions and thus were assigned with the mean value of the weights of the two (the weights are given in table 2.5).

Table A.2: The Table below shows the alignment of CDP ACS classification and the classification done by Oliver Wyman consulting firm and the percentage of emissions for each sector.

Oliver Wyman and CDP	CDP ACS	Sector Type	Emission Percentage
Electric Utilities	Power generation	Manufacturing	8.2%
Transport Services	Transportation services	Non-manufacturing	6.0%
Services	Services + Financial services	Non-manufacturing	20.1%
Agriculture	Food beverages and agriculture	Manufacturing	4.7%
Transport OEMS + Manufacturing + Capital Goods	Manufacturing	Manufacturing	17.3%
Cement + Steel + Metals and Mining + Chemicals	Materials	Manufacturing	14.9%
Real estate and construction	Infrastructure	Both	6.8%
Others + oil and gas	Other + Apparel + Hospitality + Retail	Both	21.9%

A.3 The Culture Mapping Tool

Based on Erin Meyer's Culture Map, an online tool was created that provides scales for each country (Meyer, n.d.). Those scales were downloaded and measurements of distances between points was used to estimate

the values of each dimension out of a 100. This was done with permission from the author (an example of a country is provided in figure A.2). The values of each country can be found in the Supplementary Material, StructureData.xlsx in worksheet "CountriesUsed".

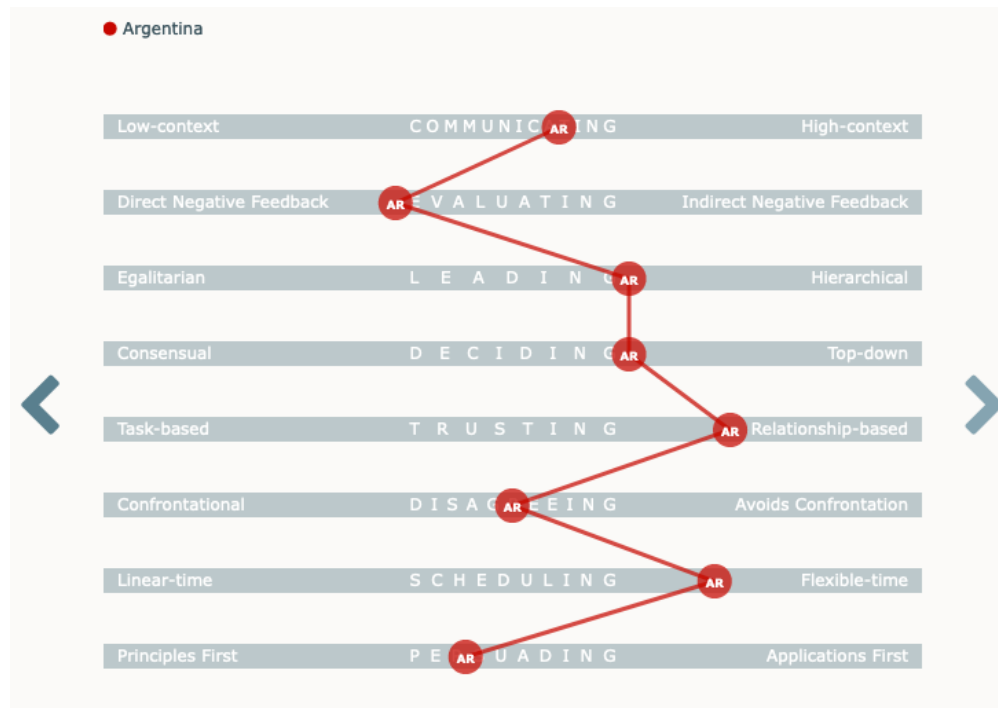


Figure A.2: Annual cumulative number of companies with approved targets and commitments between 2015–2021 (Taken from SBTi, [n.d.-b](#)). The values used are taken from the interactive infographic of the website.

A.4 Mean duration between commitment and set target

The SBTi does not provide data regarding the time separation between a company's commitment and the accepted submission of their set target. This data is important for the ABM model since it tries to simulate the process from commitment to submission, which has a deadline of 24 months.

The estimation process is based on the data taken from figure A.3. The publicly available data is the cumulative number of commitments and targets each year starting from 2015 (SBTi, [2022](#), p.11). It has to be noted that the figure does not focus on the high-impact companies but the progress of all the memberships. The goal is to find the average time from commitment to setting a target.

The approach taken is the following:

- Companies can take up to two years to set a target after making a commitment. Thus, targets are assumed to be set either 2 years after commitment, 1 year or instantly (the same year).
- First the targets set per year are assigned to the commitments made two years ago.

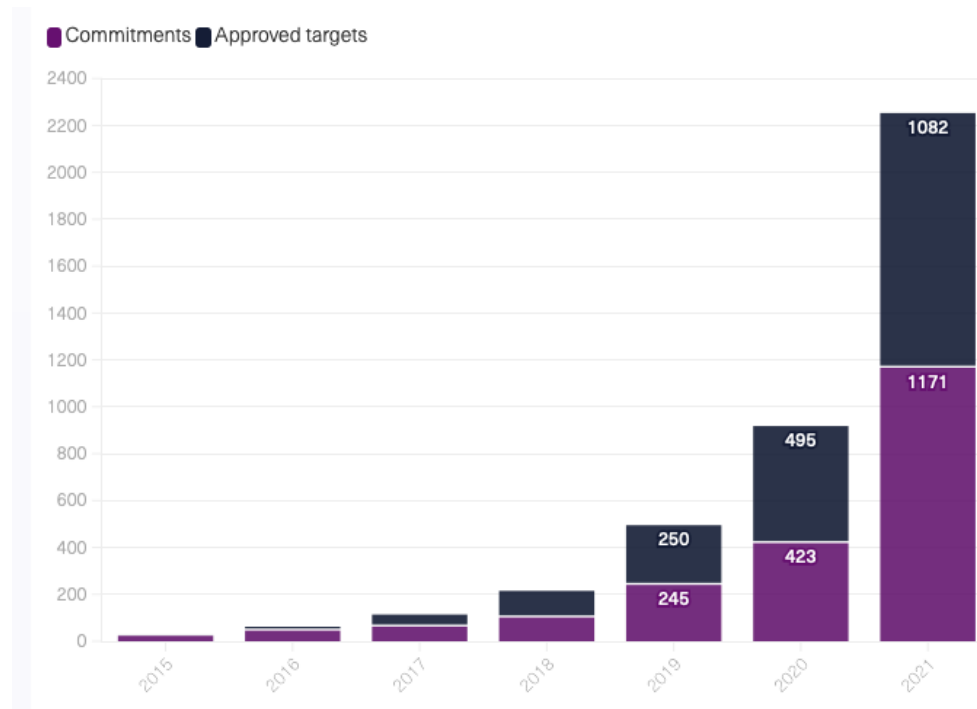


Figure A.3: Annual cumulative number of companies with approved targets and commitments between 2015–2021 (Taken from SBTi, [n.d.-b](#)). The values used are taken from the interactive infographic of the website.

- If a number of companies with targets remain, they are assigned to the commitments made one year ago.
- If there are still targets remaining, they are assigned to the commitments made in the same year.
- In order to find the average time between commitment and setting a target, the number of targets set due to commitments made the same year, one year ago, and two years ago, are multiplied by 0, 1, and 2 respectively. The total time (in years) is divided by the total number of targets set.

The above calculation gives us an average time of 0.53 years (6.4 months or steps in the model) taken to set a target by 2020, which is the year before the focused campaigns for high-impact companies begin. The average time goes down further when the CDP-SBTi high-impact companies begin in 2021 to 0.41 years (4.9 months) to set a target. The results are given more analytically in Table A.3. The calculations can be found in the Supplementary Materials, in the excel file StructuredData.xlsx, in the worksheet "Average time to set target".

Year	Cumulative Commit- ments	Commitments (Same Year)	Commitments Left (1 Year Ago)	Commitments Left (2 Years Ago)	Cumulative Targets Set	Targets Set (same year)	Estimated 0-Year Targets	Estimated 1-Year Targets	Estimated 2-Year Targets
2015	28	28	-	-	-	-	-	-	-
2016	50	22	28	-	12	12	-	12	-
2017	67	17	22	16	47	35	-	19	16
2018	106	39	17	3	109	62	42	17	3
2019	245	139	39	0	250	141	102	39	-
2020	423	178	139	0	495	245	106	139	-
2021	1171	748	178	0	1082	587	409	178	-

Table A.3: Average time taken by companies to set targets after commitment.

Table A.4: Top 15 Countries Based on SBTi Report's Total Column

Country	SBTi Report					Model				
	Total	Committed	Set Target	Committed %	Set Target %	Total	Committed	Set Target	Committed %	Set Target %
USA	533	168	95	31.5%	17.8%	565.1	141.2	123.4	25.0%	21.8%
China	230	10	8	4.3%	3.5%	238.4	35.0	19.4	14.7%	8.1%
Japan	230	71	25	30.9%	10.9%	245.2	47.5	2.8	19.4%	1.1%
India	81	17	8	21.0%	9.9%	84.9	13.5	5.9	15.9%	6.9%
Canada	95	13	10	13.7%	10.5%	99.7	25.3	21.6	25.4%	21.7%
Germany	72	31	13	43.1%	18.1%	76.4	21.4	17.7	28.0%	23.2%
France	69	45	17	65.2%	24.6%	73.0	18.7	14.8	25.6%	20.2%
UK	84	49	29	58.3%	34.5%	88.8	22.6	18.5	25.5%	20.8%
South Korea	85	7	5	8.2%	5.9%	90.5	15.0	11.7	16.6%	12.9%
Australia	51	10	6	19.6%	11.8%	53.1	13.6	11.4	25.6%	21.4%
Brazil	42	10	6	23.8%	14.3%	43.9	9.4	5.2	21.4%	11.9%
South Africa	41	6	3	14.6%	7.3%	43.2	9.7	8.1	22.5%	18.8%
Switzerland	41	19	9	46.3%	22.0%	43.8	12.3	10.9	28.0%	25.0%
Italy	24	10	7	41.7%	29.2%	25.0	5.6	4.1	22.4%	16.3%
Indonesia	24	0	0	0.0%	0.0%	26.3	3.1	1.2	11.6%	4.6%