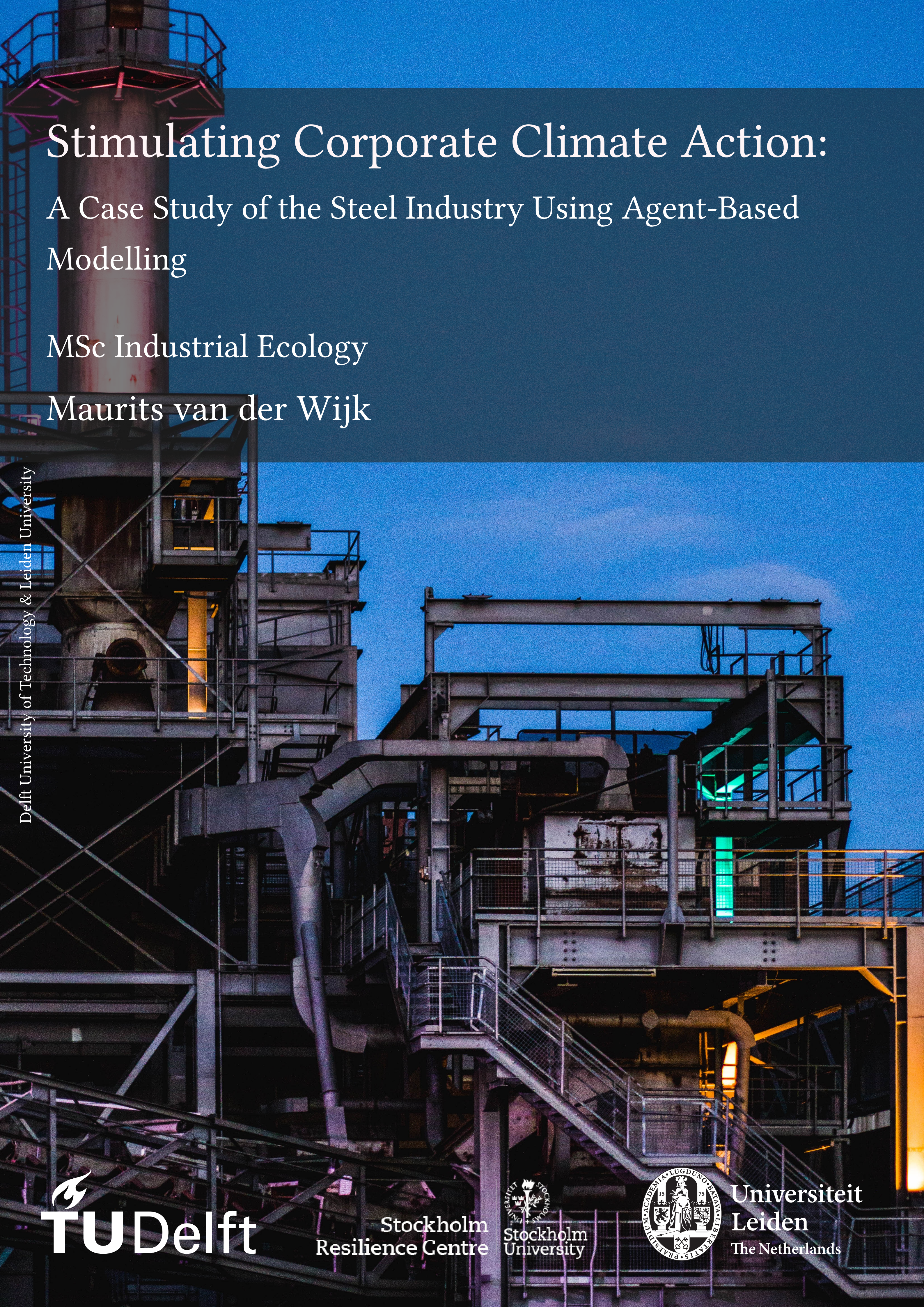


Stimulating Corporate Climate Action:

A Case Study of the Steel Industry Using Agent-Based Modelling

MSc Industrial Ecology

Maurits van der Wijk

Delft University of Technology & Leiden University

TU Delft

Stockholm Resilience Centre

Stockholm University

Universiteit Leiden
The Netherlands

Stimulating Corporate Climate Action: A Case Study of the Steel Industry Using Agent-Based Modelling

by

Maurits van der Wijk

Master Thesis

submitted in fulfilment of the requirements for the

Master of Science

in Industrial Ecology

at Delft University of Technology and Leiden University

Student number TUD:	5662028
Student number LU:	3265250
Submission date:	October 24, 2023
1st supervisor:	Dr. A. Ghorbani - TU Delft
2nd supervisor:	Prof.dr. K. Blok - TU Delft

An electronic version of this thesis is available at http://repository.tudelft.nl/.

Executive summary

By now there is an extensive body of scientific work showing that the climatic system is changing due to the influence of humans. Globally, most countries accept that change is necessary, pledging to decrease the greenhouse gas emissions (GHGs) that result from activities within their borders. However, there exists a large gap between the emission reductions that are necessary and those that are recorded in current policies. As a consequence, the spotlight for action is shifting towards the corporates that are responsible for large amounts of the emitted GHGs. Cooperatives that transcend rigid country borders are being formed as a means to stimulate more environmental pro-activity in the business sector. One of these organisations is the Science Based Targets initiative (SBTi). This organisation stimulates companies to set decarbonisation targets that are in line with the scientific consensus of what is needed to limit temperature rise to 1.5℃. Research has shown that companies setting targets together with the SBTi allocate more resources towards actually cutting emissions after doing so. As such, the number of companies committing to set science-based emission reduction targets (SBTs) is believed an adequate quantifiable metric for target-based corporate climate action.

The current pro-climate efforts of companies are not yet sufficient to limit global warming to the level agreed in the Paris Agreement. This thesis therefore explores *how companies can be stimulated to commit to science-based greenhouse gas emission reduction targets*. In order to study this, an agent-based modelling (ABM) approach is taken. This method allows to include a high level of heterogeneity among companies and adequately model the complex adaptive system that companies in a sector are part of. Since no previous ABMs have been developed that focus on target-based climate action among companies, this study takes a novel scientific direction. To limit the scope of the research, the ABM method is applied to a single industry. Research has shown that particularly the most emission-intensive companies and non-European firms are trailing behind when it comes to setting SBTs. Considering that the production of steel is responsible for approximately eight percent of anthropogenic emissions and most of the sector's production happens in Asia, the steel industry was chosen as case for this work.

The decision-making of the included companies was modelled following the Theory of Planned Behaviour. A multitude of scenarios were then simulated, which resulted in a number of novel and interesting findings. First of all, no evidence was found supporting the claim that companies perceive it a substantial competitive advantage to be a first-mover regarding SBT adoption. Rather, companies are found to only commit when they believe the necessary emission reductions are both achievable and worthwhile. Presently, the market for green steel is only just emerging, resulting in the majority of commitments happening further in the future. Model results further imply that commitments are often stalled because important socio-technological factors like the availability of renewable electricity are not present at adequate levels. Once the prerequisites of decarbonisation in line with 1.5℃ warming are developed, the number of commitments among companies is found to rise rapidly. The SBTi can enhance this by focusing on developing trust and cooperation among steel companies. The initiative could do so by utilising the networks - of both steel companies and other stakeholders - it has built in recent years and initially targeting more receptive companies such as those with older assets. By working together, firms are believed able to enhance their innovativeness, reduce the competitive risk and create the system change that is needed.

Additionally, the influence and behaviour of other stakeholders is also found to be substantial. The scenario outcomes show that steelmakers are more positive towards setting SBTs in regions where the financial pressure from carbon pricing is significant. Ensuring that low-carbon alternatives become competitive with the products of the status-quo is therefore one of the important roles that governments can play. Moreover, by providing the monetary means to invest in low-carbon technologies, financial institutions can play their part in the transition towards a decarbonised industry. As owners and financiers, these organisations can furthermore exert pressure on the companies that they are invested in to set emission reduction targets with the SBTi. Simultaneously, environmental action groups can play a key role in areas where climate change is not yet perceived as an urgent topic. By creating awareness on the problem and appreciation for the low-carbon solutions, such stakeholder groups can stimulate the contextual changes that are imperative for a successful transition.

The alignment between this study's findings and empirical contexts show that ABM can be a useful tool to assess target-based corporate climate action. As such, the ABM developed in this study can be used as a foundation for future models. By including other industries and regions, it can be used to make policy-making and resource allocation processes more effective. By utilising the constructed model and developing future iterations, stakeholders can thus assess how to most adequately stimulate science-aligned GHG emission reductions among companies.

Acknowledgment

I would like to express my gratitude to a number of individuals that made this research possible.

First of all, I want to thank my supervisors Dr. Amineh Ghorbani and Prof.dr. Kornelis Blok. Their feedback, guidance and constructive criticism throughout the research process have been tremendously helpful. In addition, I'm grateful for the opportunity to conduct my research while abroad at the Stockholm Resilience Centre. My time in Sweden has been academically and personally rewarding and I want to thank especially Dr. Sarah Cornell and Daniel Avila-Ortega for providing me a spot at the SRC. For the interesting discussions and supportive feedback, I also want to personally thank Dr. Romina Martin and Dr. Nanda Wijermans.

For the enriching time that I have had at Delft University of Technology and Leiden University, I would like to thank all those who teach in and facilitate the Industrial Ecology programme. Finally, I want to thank my family for enabling me to go to university and my friends for always being supportive and critical.

Contents

Executive summary **i**

List of Tables **vii**

List of Figures **x**

Acronyms **xi**

1 Introduction **1**

1.1 Research problem 1

1.2 Research objective and questions 3

1.3 Scope 5

1.4 Relevance of this study in the context of Industrial Ecology 9

1.5 Outline of this study 9

2 Research Method **10**

2.1 Research approach 10

2.2 Review of existing models 11

2.3 Research framework 12

2.4 Theoretical framework 14

3 Sustainability in the steel industry **17**

3.1 The current steel sector 17

3.2 Technological feasibility of low-carbon steel 19

3.3 Factors that drive environmental performance among firms 23

3.4 Conclusion 29

4 Science Based Targets and the SBTi **30**

4.1 Science-based targets to reduce emissions 30

4.2 Introduction and role of the SBTi 31
4.3 Engagement strategies (levers) of the SBTi 34
4.4 Conclusion 35

5 Conceptualisation and formalisation of the agent-based model 36
5.1 Conceptual model 36
5.2 Evaluating the model 48
5.3 Experimental setup 51
5.4 Conclusion 58

6 The Base Model 59
6.1 Defining the base model 59
6.2 Outcome of the base model 60
6.3 Sensitivity results 65
6.4 Conclusion 67

7 Results 68
7.1 Exploratory experiment results 68
7.2 Scenario results 74
7.3 Conclusion 84

8 Discussion & conclusions 85
8.1 Validating the use of agent-based modelling 85
8.2 Answering the main research question 87
8.3 Recommendations 90
8.4 Societal contribution 92
8.5 Reflections 94
8.6 Limitations & future research 95

References 105

A ODD model description 106
A.1 Model purpose 106
A.2 Entities in the model, their attributes and their temporal and spatial limits 107
A.3 Outline of the processes and model scheduling 109
A.4 Design concepts of the ABM 110

A.5 Initialisation and input data 115
A.6 Description of sub-models 134

B Weights **135**

C Sensitivity results **138**

D Variables and parameters **143**

E Companies **146**

List of Tables

1.1 Geographical scope 7

5.1 Overview of a few of the most relevant model parameters. *See Appendix D for more of the most relevant company-specific model parameters* 41
5.2 Overview of a few of the most relevant model parameters *See Appendix D for more of the most relevant model-specific model parameters.* 41
5.3 Overview of the parameters (from literature and model specific) and parameter variations used in the sensitivity analysis 52
5.4 Weights for the baseline model and different exploratory scenarios (coloring used to indicate the different TPB constructs: attitude , subjective norm and behavioural control) 55
5.5 Carbon prices used (Source: IEA (2022b)) 58

A.1 Time between decision moments for companies in each respective country. 108
A.2 Average share of women on corporate boards (%) *Note: (e) = estimated* 120
A.3 Overview of the average number of directors in a corporate board across countries . . 123
A.4 The average and standard deviation of board ages in the studied regions 124
A.5 Distribution of ownership types per proxy country 126
A.6 Estimated scrap intensity for present and future (Source: data from WorldSteel (n.d.) and World Steel Dynamics (2020)) 131
A.7 Shares of renewables in countries' electricity mix (Source: IRENA (2020)) 131
A.8 Environmental Performance Index scores per country for 2022 (Source: Wolf et al. (2022)). 134

B.1 Weights used in the baseline model 137

List of Figures

1.1 The nine planetary boundaries and the quantified impact of human activity on each (Source: Richardson et al. (2023)) . . . 2
1.2 Steel production per geographical region (Source: Eurofer (2022)) . . . 6

2.1 Constructs and relations in the Theory of Planned Behaviour (Source: Azjen (2019)) . . 15

3.1 Worldwide production of steel and use per demand sector for 2019 (Source: IEA (2020)) 18
3.2 Depiction of the two main steel-making routes and their share in global production (Source: Arens (2016) and IEA (2020)) . . . 19
3.3 Normal distribution of the age of steel-making capacity across regions (Source: based on data from GID (n.d.)) . . . 22
3.4 Share of electricity generation using low-carbon sources for the different regions (Source: LowCarbonPower (n.d.) and IRENA (2020)) . . . 24
3.5 Expected end-of-life availability of scrap steel (Source: WorldSteel (2021a)) . . . 24

4.1 Global diffusion of targets validated by the SBTi (Source: data from SBTi (n.d.[b])) . . . 31
4.2 Number of companies committing or setting targets per month since January 2016 (Source: data from SBTi (n.d.[b])) . . . 32
4.3 Steps towards SBTi certified targets (Source: adapted from SBTi (n.d.[a])) . . . 33

5.1 Schematic overview of the most important model variables, parameters and relations . 38
5.2 Simplified overview of the most relevant interactions in the model . . . 38
5.3 Flowchart of model and decision-making procedure . . . 42
5.4 Overview of agents' process to determine their attitude towards SBT adoption . . . 43
5.5 Overview of agents' process to determine the social pressure favouring SBT adoption . 45
5.6 Overview of agents' process to determine their control over achieving potential . . . 47

6.1 Effect of altering the long term threshold of companies - by varying the value for *Standard_threshold* between 30 and 45 . . . 60
6.2 Describing sub-figures for the baseline scenario . . . 61
6.3 Comparison characteristics for the baseline scenario . . . 62

7.1 Figures depicting the commitments and commitment-gap for the exploratory ownership scenarios . . . 69
7.2 Figures depicting the commitments and commitment-gap for the exploratory scrap intensity scenarios . . . 70
7.3 Figures depicting the commitments and commitment-gap for the exploratory size classification scenarios . . . 71
7.4 Figures depicting the commitments and commitment-gap for the exploratory weights scenarios . . . 72
7.5 Figures depicting the commitments and commitment-gap for the carbon pricing scenarios 76
7.6 Committed companies in the stakeholder scenarios, visualising the effect of variable changes . . . 77
7.7 Figures depicting the stakeholder scenario where both the pressure from general stakeholders (*Stakeholder_pressure*) and that from owners (*Ownership_pressure*) is increased by 30% - the stakeholder scenario that results in the highest number of commitments . 79
7.8 Committed companies in the network scenarios, visualizing the effect of variable changes 80
7.9 Figures depicting the network scenario with the baseline number of links, base importance for the behaviour of allies and a significant increase in trust - the combination that results in the highest number of links . . . 82

A.1 Inventory of proportional GHG emissions per sector for California (Source: California ARB (2020)). . . . 117
A.2 Projected carbon price (CP) and perceived carbon price (PCP) per relevant area (Source: Author). . . . 119
A.3 Normal distributions of the share of women on corporate boards, per country (Source: Author). . . . 121
A.4 Visualisation of the effect of firm size on the share of women in a company's board (Source: Author). . . . 121
A.5 Estimated increase in the share of women on corporate boards, per country (Source: Author). . . . 122
A.6 Comparison of board ages across regions (assumed normal distribution) (Source: Author). 125

A.7 National values for the used Hofstede dimensions (Source: data from Insights (n.d.)). . 127
A.8 Net income and net income change for ArcelorMittal over the last ten years (Source: MarketScreener (n.d.[a])) . . . 128
A.9 Example of random *Financial_performance* progression in the model . . . 129
A.10 Estimation of scrap availability for 2020 and 2050 (Source: adapted from WorldSteel (2021b)). . . . 130
A.11 Estimate of the future production quantities of crude steel (Source: World Steel Dynamics (2020)). . . . 130
A.12 Normal distribution of the age of steel-making capacity across regions (Source: based on data from GID (n.d.)). . . . 132
A.13 Country level steel production in 2021 (Source: WorldSteel (n.d.)). . . . 133

C.1 Effect of altering the value for *Create_links* . . . 138
C.2 Effect of altering the value for *Financial_performance_change* . . . 139
C.3 Effect of altering the value for *Large_size_threshold* . . . 139
C.4 Effect of altering the value for *Medium_size_threshold* . . . 140
C.5 Effect of altering the value for *Price_threshold* . . . 140
C.6 Effect of altering the value for *Size_effect_board* . . . 141
C.7 Effect of altering the value for *Size_effect_diversity* . . . 141
C.8 Effect of altering the value for *Threshold_mp* . . . 142

D.1 Overview of the most relevant global variables and parameters of the model . . . 144
D.2 Overview of the most relevant company-specific variables and parameters of the model 145

E.1 Companies included in the model - part I . . . 147
E.2 Companies included in the model - part II . . . 148
E.3 Companies included in the model - part III . . . 149

Acronyms

Acronym	Full term
ABM	Agent-based model
BAT	Best available technology
BF-BOF	Blast furnace - basic oxygen furnace
CBAM	Carbon border adjustment mechanism
CAS	Complex adaptive system
CCS	Carbon capture and storage
CO2	Carbon dioxide
DRI	Direct reduced iron
EAF	Electric arc furnace
EAG	Expert advisory group
EPI	Environmental Performance Index
ETS	Emissions trading system
GHG	Greenhouse gas
ICI	International cooperative initiative
NGO	Non-governmental organisation
ODD	Overview, Design concepts and Details protocol
OFAT	One-factor-at-a-time
SBT	Science-based target
SBTi	Science Based Targets initiative
SME	Small and medium-sized enterprise
TRL	Technology readiness level

Chapter 1

Introduction

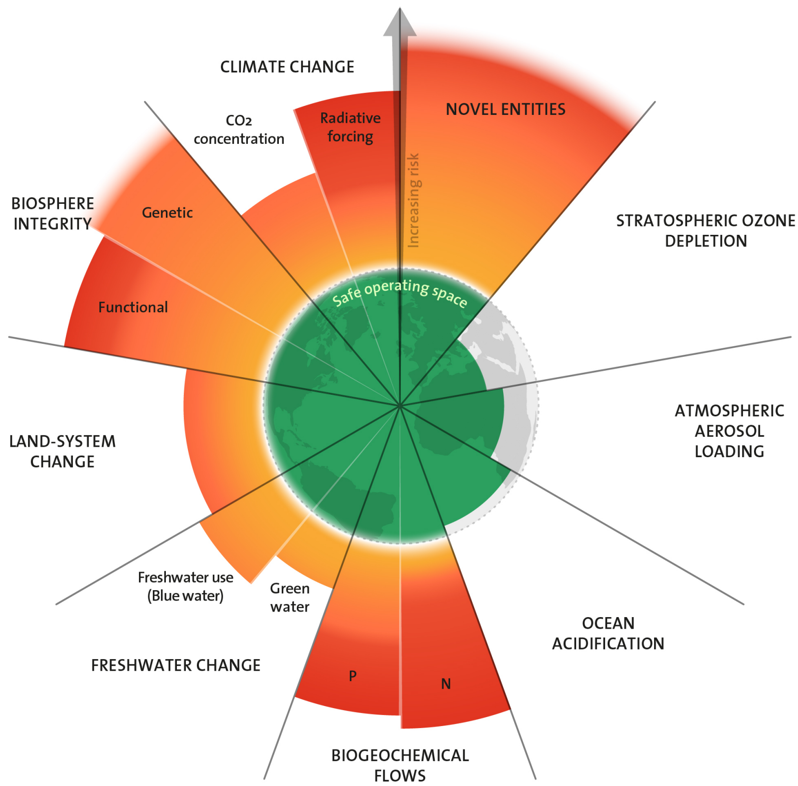
1.1 Research problem

Society is facing climatological and ecological crises due to immense pressure that anthropogenic activities place on the Earth system. The result of humanity's distorted relation with the biosphere has increasingly persistent impacts on natural ecosystems, human settlements and global infrastructure (IPCC, 2022). Recently, scientists conducted and published the first full assessment of the nine planetary boundaries - a framework that quantifies the anthropogenic impact on the Earth system and to what extent this places society at risk (Richardson et al., 2023). The study concluded that six out of the nine boundaries have been transgressed globally, while more are breached on local levels (Figure 1.1).

The planetary boundary that at present receives most attention, is climate change. Caused by the emitting of greenhouse gas emissions (GHGs) and the destruction of natural carbon sinks, the challenge of limiting global warming is far from adequately being managed. Whereas it is a global aim, as recorded in the Paris Agreement, to limit warming to 1.5℃, current policies and efforts are set to result in over 2℃ warming by the end of the 21st century (NewClimate Institute, 2022). On top of that, the most realistic scenarios that limit warming to 1.5℃ include critical periods where the temperature overshoots this threshold. The risk that the Earth system is shifted into another - less stable and hospitable - state is increased with every bit of warming, especially if global temperature rise overshoots the 1.5℃ boundary (Wunderling et al., 2023).

At the same time, extreme weather events are already more generally occurring, with all associated negative repercussions such as droughts, wildfires and heavy precipitation. About half of all species have already shifted their habitat more towards the poles or higher elevations, to escape the effects

Figure 1.1: The nine planetary boundaries and the quantified impact of human activity on each (Source: Richardson et al. (2023))



of global warming. Worryingly, such present day consequences of climate change frequently exceed the predictions from past assessments (IPCC, 2022). Understanding that climate change is a non-linear process that will not only affect the natural, but also the socio-economic system, there is a growing need and urgency to coordinate global action (Baptista et al., 2022).

The most concrete example of such in recent years has been the inception of the Paris Agreement. Regrettably, national policies aimed at reducing GHG emissions are found to fall substantially short of the goals defined in Paris (Roelfsema et al., 2020). Moreover, the non-binding nature of the nationwide emission reduction objectives has stimulated a global economic game with low trust, in which most nations choose for the short-term that they believe best for themselves. The result is a prisoners dilemma that in environmental sciences is better known as the tragedy of the commons.

Following the global inaction of most countries, attention for climate action is increasingly shifting towards the corporate sector. Much of the current stress on the environment is linked to economic activity, specifically from the world's largest companies. Increasing levels of market concentration have resulted in multinational conglomerates that have the ability to influence politics, inhibit sustainable innovation and coerce suppliers into cost-cutting practices for which nature pays the price (Fuchs et al., 2009).

Acknowledging the power and responsibility that certain companies hold, there is a growing consensus that involving businesses in the societal sustainability debate is the way forward (Barbier et al., 2018). Engaging with these players can be challenging, however, and it is largely uncertain how companies respond to different stakeholder pressures. According to Widerberg et al. (2015), International Cooperative Initiatives (ICIs) can be helpful in establishing the governing conditions that are important for increased climate action. ICIs are collaborative efforts among organisations and stakeholders to achieve a common objective. Concerning climate change specifically, research shows that by combining the ambitions of global initiatives, ICIs have the potential to reduce the emissions gap to under 2℃ (Lui et al., 2021). When it comes to climate action, one of the most well-known ICIs is the Science Based Targets initiative (SBTi). Focused on aligning the environmental sciences, particularly related to climate change, with the decarbonisation goals of the private sector, it devises science-based (i.e. in line with the Paris Agreement) targets (SBTs) for organisations. The drivers behind companies' decisions to set SBTs are not quite clear, though evidence has been found that companies with SBTs increase their climate action efforts (Bjørn et al., 2022). Regrettably, commitment to science-based targets in heavily polluting industries is falling behind, while exactly these sectors cause a large share of the global emissions (Bjørn et al., 2022; Giesekam et al., 2021). Considering that companies adopt behaviour and investment strategies that focus on reducing emissions when they adopt SBTs (Freiberg et al., 2021), the number of SBTi committed companies can be used as an effective metric to assess how companies can be stimulated to increase their climate action. As such, there is a direct need to assess how more firms can be motivated to set GHG reduction targets. In doing so, there should be an explicit focus on the companies falling behind of their counterparts when it comes to science-based target setting – i.e. the largest emitters, small-and-medium-sized enterprises (SMEs) and companies outside of the European region (Giesekam et al., 2021).

1.2 Research objective and questions

Taking into account that it is unclear what exactly drives or inhibits the setting of SBTs among most companies (Bjørn et al., 2022), it is necessary to gain a better understanding of corporates' motivations for climate action. With that information, this study can assess what the most effective incentivisation methods are to encourage SBT adoption among companies in the heaviest polluting industries. Since Freiberg et al. (2021) find that firms actually reduce their emissions when they have committed to doing so using SBTs, this study considers commitment to the SBTi as a metric for - target-based - climate action and uses both terms interchangeably.

Moreover, the SBTi is a focal point in this study as this particular initiative is the main authority on science-based target setting to reduce companies' GHG emissions. At present, it is also the most popular ICI that focuses both on companies and climate action (Giesekam et al., 2021). Through its operations, the initiative seeks to align businesses' GHG emission reduction targets with the most recent scientific consensus of what is necessary to mitigate over 1.5℃ global warming. Though certain companies already have internal targets, Giesekam et al. (2021) point out that the initiative can bring a lot of value by ensuring that those targets are aligned with the most recent science on climate change. With that in mind, this study aims to answer the following research question:

How can companies be stimulated to commit to science-based greenhouse gas emission reduction targets as set by the SBTi?

In order to know in which way companies can be motivated to define science-based targets, it is important to outline the drivers and barriers to such commitment, which until now remain relatively unclear (Bjørn et al., 2022). Particularly, there is a need to better understand company decision-making procedures on decarbonisation. With the first sub research question, it is therefore the aim to express which company features could be beneficial towards undertaking climate action, and which could have the opposite effect:

Sub-question I: Which company and environmental characteristics are important for companies in their decision-making procedure regarding target-based climate action?

Moreover, since this research is conducted with a focus on the SBTi, it is important to gain a better understanding of the initiative. Specifically, there should be a focus on gaining insight into the current business engagement methods of the SBTi:

Sub-question II: How does the SBTi currently motivate companies to commit to science-based emission reduction targets through its operations?

With this understanding, it can be assessed which activities are most fruitful to ensure companies commit to decarbonisation. For a comprehensive and in-depth recommendation on what is most effective to stimulate further corporate climate action, it is relevant to evaluate and compare the potential effect of different scenarios:

Sub-question III: What is the impact of different scenarios of company behaviour, stakeholder intervention and government stimulation on SBT adoption among companies?

1.3 Scope

Sectoral scope

Considering that the outlined research questions are broad in nature, for example encompassing all possible firms, this research takes a case study approach to develop the necessary answers. Acknowledging the types of companies that are lagging behind when it comes to SBT adoption (as was discussed in Section 1.1), this study focuses specifically on the steel sector.

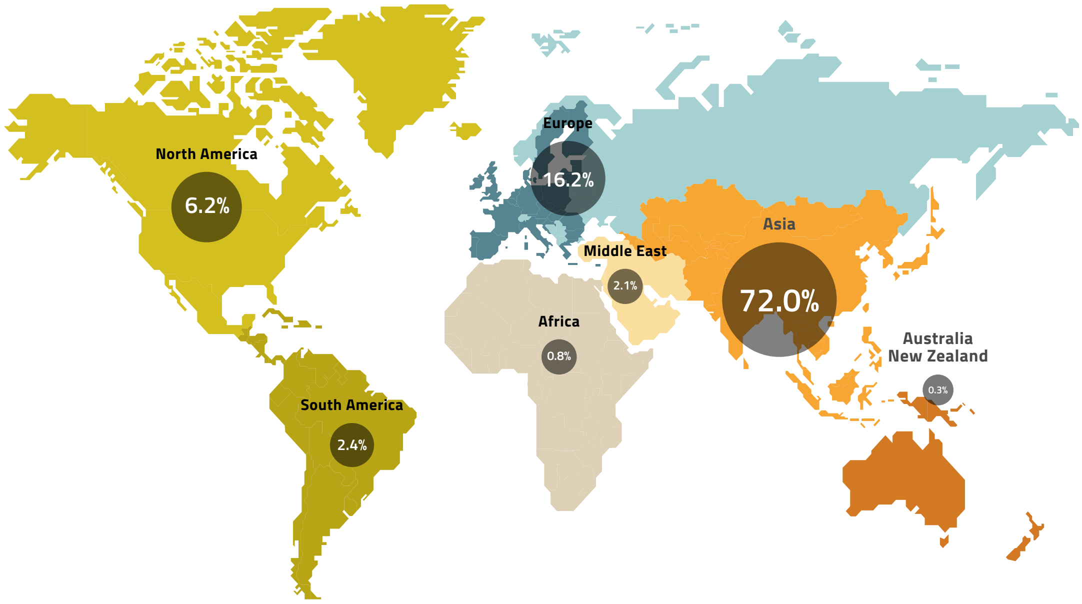
The production of steel results in 28% of all emissions directly associated with industry, or 7-9% of all anthropogenic GHG emissions worldwide (WorldSteel, 2021a). With a growing world population and increasing global development, steel production will still be increasingly important in the coming decades. Due to its sheer necessity, even certain modelling scenarios focused on limiting global warming to 1.5℃ incorporate growth projections for the worldwide steel industry (B. Chan, 2022).

With steel production resulting in such a large share of global emissions, it is also one of the sectors with heavy emitters that until now have refrained from setting SBTs (Bjørn et al., 2022). In line with that, the SBTi notes that a mere 14 steel companies made commitments or set SBTs by March 2022. Studying the current data, it seems that this number has approximately doubled, though most of the largest companies have yet to commit. The SBTi therefore recognises the importance of growing the number of committed heavy emitters in order to adequately address the climate crisis (SBTi, 2022a). The initiative does however believe that the adoption of SBTs by 20% of companies in a given industry results in the rapid commitment by the remaining industry members (SBTi, 2022a). Nonetheless, data presented by the initiative further substantiates the claims made by Giesekam et al. (2021) that SBT commitment is a phenomenon occurring mostly in Europe. For steel specifically, of the 14 companies mentioned previously, eight are European (B. Chan, 2022). A quick glance at the steel market further shows that more than 70% of global production takes place on the Asian continent alone (WorldSteel, 2021a). Where the SBTi thus concludes that the critical threshold of adoption among 20% of what they call 'high-impact companies' is surpassed (SBTi, 2022a), the numbers differ largely per sector. Looking at their defined 'Materials' sector – which includes steel companies – a total of 75 high-impact companies (29% of the total in this sector) have made commitments. This is only minimally above the 20% critical mass hypothesised by the initiative. As mentioned before though, most of the commitments are from European firms. Even more important, this 'Materials' sector does not only include steel, but also, among others, those companies producing cement, developing chemicals and mining minerals (CDP, 2022b). Whereas a critical mass may thus have been reached among general high-impact materials companies in Europe, it is important that also the steel companies in other regions commit to SBTs.

Geographical scope

When looking at the global dispersion of steel production (Figure 1.2), it becomes apparent that the most important regions are Asia, Europe and North America. Since literature suggests that European firms more generally have already set SBTs, opportunities for commitment likely exist on the first and last mentioned continents.

Figure 1.2: Steel production per geographical region (Source: Eurofer (2022))



The steel industries of Asia, Europe and North America combined manufacture approximately 94.4% of global steel output (see Figure 1.2). The other regions – South America, Africa, Middle East and Australia New Zealand – at present produce such small amounts on a global scale that they are not further considered in this work. Note however, that the nation of Turkey is included in Europe, as this is done by Eurofer (2022) in their numbers, though they did not depict it this way in their map[1]. Since the aforementioned three regions cover a wide number of countries – with substantially differing ambitions, policies and cultures – they are represented by using a number of proxy countries (Table 1.1).

[1]More specifically, the map (Figure 1.2) indicates that the Middle East produces 2.1% of global steel output. Eurofer (2022) reports that in numbers, that would be approximately 40.7 Mt of crude steel. However, their map colours a number of countries, including Turkey which produced 40.4 Mt of steel already by itself in 2021. Including Turkey in the Middle East region would thus entail that the other countries in this region barely produced anything. Yet the opposite is true, with countries like Iran (28.3 Mt) and Saudi Arabia (8.7 Mt) manufacturing considerable quantities (WorldSteel, n.d.). Similarly, Eurofer (2022) suggests that non-EU European countries produced 155.9 Mt in 2021. Large steel producers in the non-EU region are Russia (77 Mt) and Ukraine (21.4 Mt), however with the other nations producing relatively small amounts of steel, the 155.9 Mt would not be reached. It therefore seems reasonable to assume that Eurofer included Turkey in the European numbers, while excluding them from the region in Figure 1.2.

Specifically, Asia is divided into China and 'Other Asia', as the former produces 75% of the continent's steel (Eurofer, 2022). 'Other Asia' is represented by India, Japan and South Korea, which make up about 21% of Asian production, or 83% of production in 'Other Asia'. Europe is separated into the EU and non-EU, where Switzerland and the United Kingdom are treated as if part of the EU[2]. The former is represented by Germany, Italy and Spain, the three largest steel producers of the bloc, whereas Non-EU is proxied by Russia, Turkey and Ukraine, which are by far the largest producers of the Non-EU region (WorldSteel, n.d.). Lastly, North America is split into the United States and 'Other-NA' – represented by Canada and Mexico.

Table 1.1: Geographical scope

Continent	Region	Note
Asia	China	
	Other Asia	Proxied by India, South Korea and Japan
Europe	EU	Includes Switzerland and the United Kingdom. Proxied by Germany, Italy and Spain
	Non-EU	Proxied by Russia, Ukraine and Turkey
North America	United States	
	Other-NA	Proxied by Canada and Mexico

Included companies

This study focuses specifically on the largest steel companies. Concretely, all steelmakers in the given geographical scope, with a production output larger than three Mt in 2021 are included in the model. Those steel companies in North America, Europe and Asia that are a member of WorldSteel and have production volumes lower than three Mt are also included. As is elaborated on in Appendix A.2, certain companies are split in the model to account for the geographical dispersion of steel production. However, other than certain smaller sized WorldSteel members and the splitted companies, there is no focus on small-and-medium sized enterprises. In other words, though Giesekam et al. (2021) found that there is a lack in commitment to SBTs among SMEs, these companies are not explicitly included in the study. Further excluded from analysis are other non-steel producing companies, such as steel-buying companies in the automotive or construction sector. As the business-to-business interaction between steel producers and steel buyers is sometimes important, this will be incorporated via stakeholder pressure. However, the full complexity of the interactions with and the interplay between companies in other sectors is outside the scope of this study.

[2]Regarding the variables considered in this study, it is assumed that the EU represents these regions better than Non-EU. For instance, the emission trading systems (ETS) of Switzerland and the EU are formally aligned and the ETS carbon price in the UK follows a similar projection as its EU counterpart.

Temporal scope

On a time-based level, this research will focus on the dynamics of SBT adoption among steel companies from the beginning of 2023 until the end of 2035. The start in 2023 is representative for when this study commences, while the period up to and including 2035 is considered reasonable to capture both the commitment dynamics between companies and limit the uncertainty that projections of the future hold (see Appendix A.2 for elaboration).

Additional notes

On top of the scope defined above, it is important to note that this study ignores all sorts of exports and imports between countries and regions. In other words, the steel imports of for example the EU and Canada are not included and neither are their incoming Carbon Border Adjustment Mechanisms. In a similar line, the international trade of steel scrap is also excluded from consideration.

Lastly, it is worthwhile to mention that this study only focuses on steel companies' decision-making process up to and until SBT commitment. Specifically, companies have a period of 24 months in which they must set SBTs after they have committed. If they do not set SBTs within this period, their commitment is dropped. However, companies can also have other reasons explaining why they un-commit from setting SBTs. In all instances, this process of 'un-commitment' is excluded from analysis as it is considered beyond the scope. Importantly, it should be noted that companies' commitment influences other steelmakers, however, a potential effect of a company's commitment on itself or other committed companies is not within the boundaries of this research.

1.4 Relevance of this study in the context of Industrial Ecology

The emission of greenhouse gases causes the global phenomenon of climate change. Thus, as GHG emissions spread through the Earth System's atmosphere, local decisions or activities have an impact on a global scale. Decreasing emissions, which predominantly come from large businesses, is therefore a challenge with global relevance. More specifically, through their extensive and global supply chains, corporations have attained high levels of power that stretch beyond the economy. Rather, a complex system of intricate connections, guided by corporates' motives, lays at the heart of the systemic misalignment between nature and society. This study therefore aims to provide novel ways of steering corporations towards reducing their impact on the global climatic system and shifting their purpose. In doing so, a complex system approach is taken, which is one of the core foundations of the field of industrial ecology (IE). Moreover, aligning with IE is the consideration and integration of various disciplines to come to a comprehensive and holistic understanding of the studied system. Lastly, the focus of this thesis on GHG emissions reduction aligns well with IE's central aspects of sustainability and combating climate change.

1.5 Outline of this study

Now that it is established what this study will look into, Chapter 2 discusses with which method the research question will be answered. The chapter furthermore discusses the relevant scientific work that has already been conducted on similar topics with the chosen method. Moreover, the theoretical foundations of this study are discussed. Chapter 3 will then discuss the current literature on decarbonising the steel industry. Following the literature review, the most important drivers and barriers to corporate climate action will be outlined. In the fourth chapter, the current operations and engagement strategies of the Science Based Targets initiative are addressed. Chapter 5 will then describe the ABM that is developed using the information of the preceding chapters by following the outline of Van Dam et al. (2012) and Grimm et al. (2020). Moreover, the experiments and scenarios for which the model will be used are discussed in detail. The results of the analyses are then mentioned. First by describing and dissecting the base model (Chapter 6) and then by discussing the experimentation results (Chapter 7). Lastly, the limitations, implications and conclusions of the research are considered in Chapter 8.

Chapter 2

Research Method

2.1 Research approach

Considering the challenges posed by real-world experimentation with companies, it is useful to take a modelling approach to study the interactions and behaviour between steel-making businesses. By using mathematical modelling, different scenarios can be programmed and assessed. Farmer et al. (2009) argue, however, that presently used mathematical models in decision-making (e.g. econometric models) are invalid to study complex adaptive systems (CAS). Therefore, studying the complexity of interactions between business entities warrants the use of a simulation approach (Greasley, 2017). Specifically, such an approach enables this study to assess company behaviour in a number of scenarios under stringent time limitations (Shannon, 1975).

Following the definition of Waldrop (1993), it is argued that the steel sector ecosystem studied in this research qualifies as a CAS. In order to provide an adequate answer to the defined research question, the simulation model should therefore i) represent the complexity of the system at hand in the best way possible and simultaneously ii) facilitate the understanding of the system through simplicity (Van Dam et al., 2012). Moreover, to study CAS it is worthwhile to take a simulation modelling approach in which system behaviour can be inferred from rules defined at a lower level. Agent-based modelling (ABM) is a tool highly adequate for this, as it enables the modeller to develop generative clarifications by dictating the lower-level rules of autonomous agents (Epstein, 2006). ABMs are further able to include the relevant interactions between agents and their environment, allowing them to encompass normative changes in a society or system (Köhler et al., 2018). The bottom-up perspective of agent-based modelling thus makes this specific method useful to simulate a complex system in which corporations are the subject of study. Using ABM, it will be possible to express the existent heterogeneity among steel companies, capture their interactions with each other and their environment, and simulate a diversity of scenarios (Macal et al., 2005).

2.2 Review of existing models

Complexity science is an upcoming field that has seen a strong growth in recent years. More and more it is acknowledged that we need to use different tools when analysing complex problems related to the social and natural world. As such, agent-based modelling is increasingly used as a transparent, informative and accessible research method that is able to encompass complexity (Van Dam et al., 2012). Though not focused on climate action or a similarly sustainability-oriented topic, Den Hartigh et al. (2005) developed a simplified model of business interactions in a network where certain companies hold a 'keystone' position. Ramkumar et al. (2022) expand on that notion by showing with ABM that in order to stimulate innovation adoption, certain players are vital in the diffusion process. Such works emphasise the necessity of modelling the interconnections between steel-making companies, but do not relate to climate action or sustainability target setting.

The use of ABM has, however, also become more prevalent in the context of reducing anthropogenic GHG emissions. Castro et al. (2020) show that a number of studies are conducted with the firm as a focal agent when studying the potential for emission reduction. However, these most often focus on company-consumer interactions. The agent-based models where firm-to-firm interactions are studied, on the other hand, mostly concern the behaviour of companies in the electricity market. These studies focus on emission reduction, however, differ from this research in that this work focuses specifically on the climate action needed to align businesses with the Paris agreement. Some of the other reviewed papers by Castro et al. (2020) study the adoption of low-carbon technologies and diffusion of novel innovations. The spillover of adequate - that is, in line with the scientific consensus of necessary climate action - mitigation behaviour is, however, not explicitly considered. Moreover, none of the studies assessed by Castro et al. (2020) explicitly study the potential influence of ICIs on corporate climate action. This study therefore aims to fill an existing gap in the current literature by modelling target-based company climate action using ABM. Specifically, this work is novel as it interprets the role of ICIs - particularly the SBTi - while modelling science-aligned emission reduction behaviour. From the literature review, it can be concluded that the focus on sustainability target setting – or more specifically, the commitment to setting science-based emission reduction targets – has not yet been studied using ABM.

2.3 Research framework

In order to answer the defined research questions, this study will take an exploratory approach. Moreover, as the developed model and experimentation will build on existing theories, which are applied to an enterprise context, this research will mostly be deductive. As a research framework, this work will build on the simulation modelling cycle presented by Van Dam et al. (2012). By going through the below described phases, it is the aim of this study to answer the defined research questions.

'Problem formulation and actor identification'

As described in the previous sections, this research work aims to provide insight into the decision-making behaviour of companies to take climate action. Specifically for heavy industry and non-European actors there is a high need for increased efforts, resulting in this study's focus on the global steel industry. The scope and research problem were defined through a literature review, the results of which were discussed in Chapter 1.

'System identification and decomposition'

In this part of the research process, it will be more explicitly defined who the relevant agents in the studied system are. Those agents have states (i.e. properties) that govern how they behave, which are outlined together with the most relevant actions and interactions of and between the agents. It is the defining of such properties and actions that enable agent-based models to provide generative answers to complex systems questions. Moreover, in this part of the modelling cycle the environment in which the agents exist is defined and the external factors influencing agent behaviour are outlined. These factors are all recorded in chapter 3.

'Concept and model formalisation'

Using the factors defined and described in the previous step, this particular phase of the research process is focused on developing a conceptual model. Following the Overview, Design concepts and Details (ODD) protocol as described by Grimm et al. (2020), the conceptual model is described for transparency and reproducibility. The model is further developed into a formalised model, by writing out the model interactions and visualising the agent decision-making process using flowcharts. This particular phase of the research process is described in Chapter 5 and Appendix A.

'Software implementation'

Carefully following the model narrative and decision-making flowcharts as defined, the model is programmed in the coding software. The agent-based simulation of this study is coded in NetLogo 6.3.0 (Wilensky, 1999) and the implementation of the model in the software is provided as a supplement to this work.

'Model verification'

Though great care will be applied when translating the conceptual model into a computational model, it is necessary to conduct some verification. Particularly, it is assessed if the programmed model accurately represents the conceptualised model. That is because the model narrative may have important implicit factors that are not recognised in the computer code. As such, they have to be made explicit in the code or acknowledged that the model's output is not directly representative of the conceptual model. Verification will be explicitly written about in Section 5.2, though it should be noted that verification is an important iterative step throughout the entire modelling process.

'Experimentation and data analysis'

In order to provide an answer to sub-question three, a number of simulations has to be run with the model. Particular details on all the simulated scenarios are defined in Section 5.3. Moreover, sensitivity tests are conducted to test the robustness of the initial findings. The outcomes of these tests are presented and discussed in Appendix C and Chapter 7 together with the results of the simulations. Particular attention goes to the discovery of potential patterns in the data, while this thesis does not aim to predict a specific amount of commitments by a certain time.

'Model validation'

Following the analysis of the data, it is important to check whether the model's outcomes seem to align with what is logical and perceived in the real world system. This is an iterative part of the programming phase, however will be explicitly mentioned in Section 5.2. Validation will be done using a combination of literature and expert opinion.

'Model use'

Lastly, the outcome of the entire study and modelled simulations is presented. The main research question is answered using the model results and the validity of the study is discussed. Based on the discussion, novel research directions are proposed, so that this work can provide the foundation for future scientific studies.

2.4 Theoretical framework

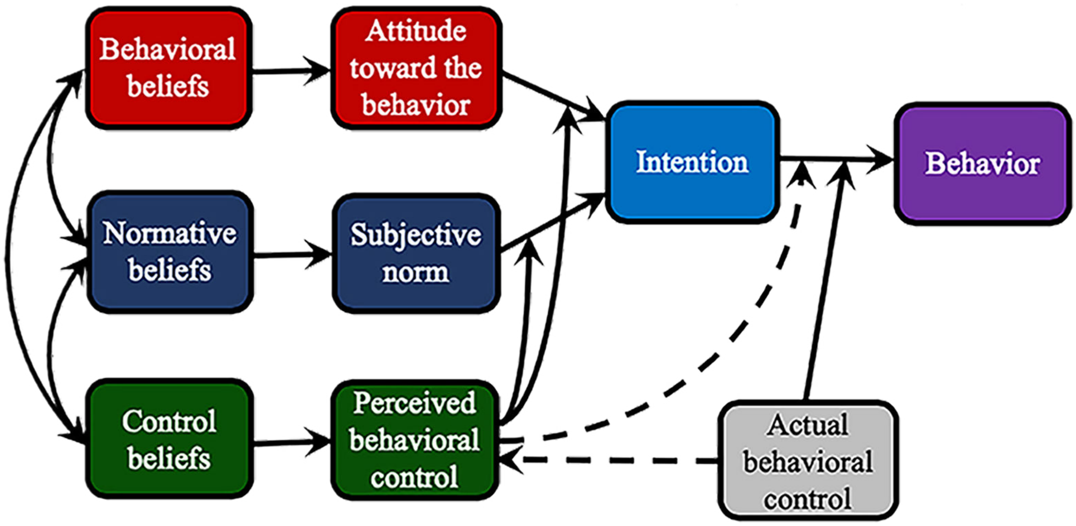
Describing the theories underlying this work is important to ensure that readers are able to understand and follow the logic underpinning this study. Moreover, clearly outlining the choices made regarding the theoretical foundations of this work, enhances transparency and allows for scrutinising where other researchers believe this relevant. The discussed theories will be elaborated on later specifically with regards to how they are included in certain elements of the ABM. Now, it is discussed what these theories are about and why these specific ones have been chosen.

A theory for agent-based decision-making

When it concerns the behaviour of human beings, a broad range of theories exist that try to explain why and how individuals make decisions. These theories, however, often have different foci and are thus relevant to differing situations. Certain behavioural theories consider the entire course of an individual's decision-making, for instance, while others relate only to one (sub)process (Schlüter et al., 2017). Moreover, when applying a theory about human behaviour to a specific context, theories leave certain gaps to be filled in by assumptions (Sawyer, 2004). In other words, decision-making theories are often not complete and need study specific interpretation and adaption. Identifying what the most relevant behavioural theory could be is therefore an important step in modelling simulations (Schlüter et al., 2017).

In order to find the theory that most appropriately represents the decision-making process of steel companies, this study looked into a broad number of theories as outlined by Constantino et al. (2021), Balke et al. (2014) and Schlüter et al. (2017). Generally, theories focused on the maximisation of utility (e.g. rational choice theory) are used to describe companies' behaviour. However, the current empirical knowledge on individuals' choice behaviour no longer aligns with this theory (Schlüter et al., 2017). Rather, Dignum et al. (2009) argue, important factors in (human) decision-making behaviour are interactions and culture, in addition to other contextual factors like policies. The authors suggest that there should be a distinction between 'goals' and 'intentions' when describing human decision-making. Considering therefore the nature of the modelled agents (i.e. corporate entities, which are in the essence operated through human decision-making) and out-datedness of specific other theories, the theory used in this study is the Theory of Planned Behaviour (TPB; Figure 2.1).

Figure 2.1: Constructs and relations in the Theory of Planned Behaviour (Source: Azjen (2019))



This theory posits that a person first develops the intention to behave, if there exists enough social pressure (i.e. subjective norm) and there is a positive attitude towards the studied behaviour. This intention, however, does not automatically translate into actual behaviour. With the existence of enough intent, individuals assess if they feel in control over the behaviour. In other words, an actor only performs an action when it has both the intent to do so and the belief that it could actually achieve the behaviour (Bosnjak et al., 2020). For this study specifically, 'behavioural control' relates to companies' perception of achieving the emission reductions necessary following science-based emission reduction targets[1].

Though the TPB is most commonly used in empirical studies, it has also been applied in modelling research focused on for instance the uptake of novel technologies and practices (Schwarz et al., 2009; Kiesling et al., 2012). Consequently, it is believed an appropriate theory to model the decision-making process of steelmakers regarding the potential adoption of SBTs.

Nonetheless, while the TPB incorporates a number of the aspects of an adequate behavioural theory, according to Dignum et al. (2009) it does not suggest the level of importance of the behaviour, opinions and pressure by others. As such, variable weighting will be used to define the importance firms give to certain factors. Moreover, a cultural dimension has been incorporated in this study to determine to what extent steel companies value for example the behaviour of other firms.

[1] Since this work uses committing to SBTs as a metric for climate action, 'behavioural control' can here also be interpreted as *the perception of companies to achieve setting SBTs.* Since committing to targets is not a process that requires much control, this study interprets the TPB construct as explained in the main text.

The cultural aspects of agent behaviour

There exist a number of theories relating to culture that could be adequate to identify cultural heterogeneity among the modelled companies. Some of the most prominent methods to differentiate between cultures include the Schwartz (2011) Cultural Value Orientations, the Culture Map developed by Meyer (2014) and the cultural dimensions outlined by Hofstede (2001). Similar to other research (e.g. Kreulen et al. (2022)), this work uses the latter because up-to-date empirical data is available for all studied countries and it has been widely applied in research acknowledging cross-cultural differences (Taras et al., 2009). As will be elaborated upon in other sections, there is a specific focus on two of Hofstede's dimensions. More concretely, this study will incorporate countries' and companies' 'Individualism vs. Collectivism' and 'Long-Term Orientation'. Using these cultural factors - in combination with the TPB - allows to model heterogeneity among the actors with regards to what they value and results in a more accurate representation of the studied system. The values for both dimensions are assumed stable over time, since the future development of culture is impossible to accurately predict.

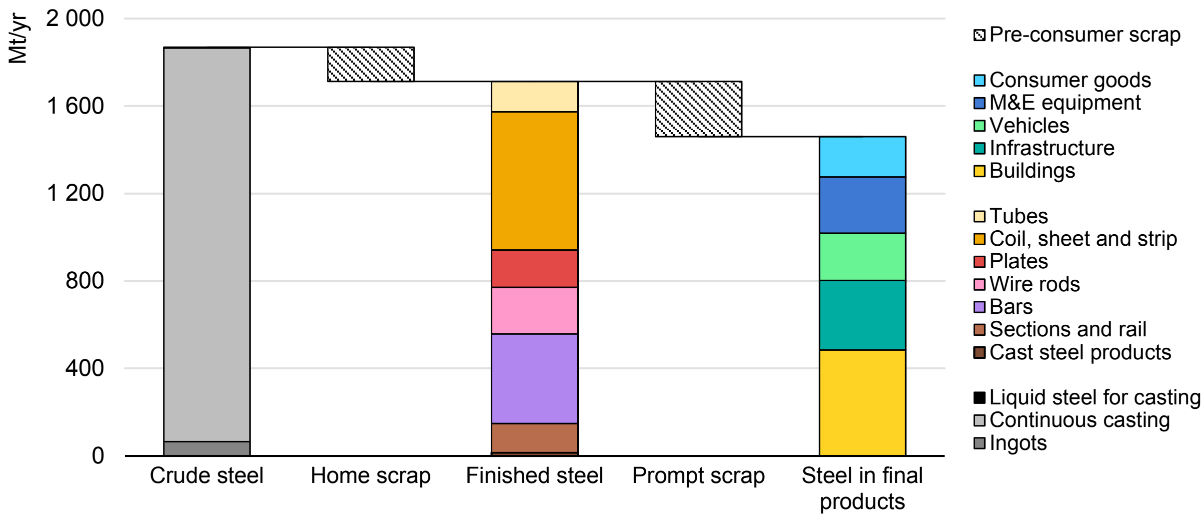
Chapter 3

Sustainability in the steel industry

3.1 The current steel sector

After cement and timber, steel is the most abundant man-made material worldwide in annual production volume. The material is mostly used in the construction of buildings and manufacturing of infrastructure, vehicles and mechanical products (Figure 3.1). Demand is often high in regions that are undergoing rapid economic development, which is why China is and has been the main global steel producing hub in recent years. In 2021, 72% of all steel produced globally came from China, with the country's largest steelmaker – China Baowu Group – individually producing more than India, the world's second largest steel-making country (WorldSteel, 2021c; Eurofer, 2022). In 2021, there were a total of 113 companies that produced at least 3 million tonnes of steel, with six of the top 10 companies coming from China. Similarly, the 6 major steel producing regions – China, EU-28, India, Japan, South Korea and Russia – together produce nine-tenths of all coal-based CO2 emissions that are related to steel-making (Arens et al., 2021).

Figure 3.1: Worldwide production of steel and use per demand sector for 2019 (Source: IEA (2020))

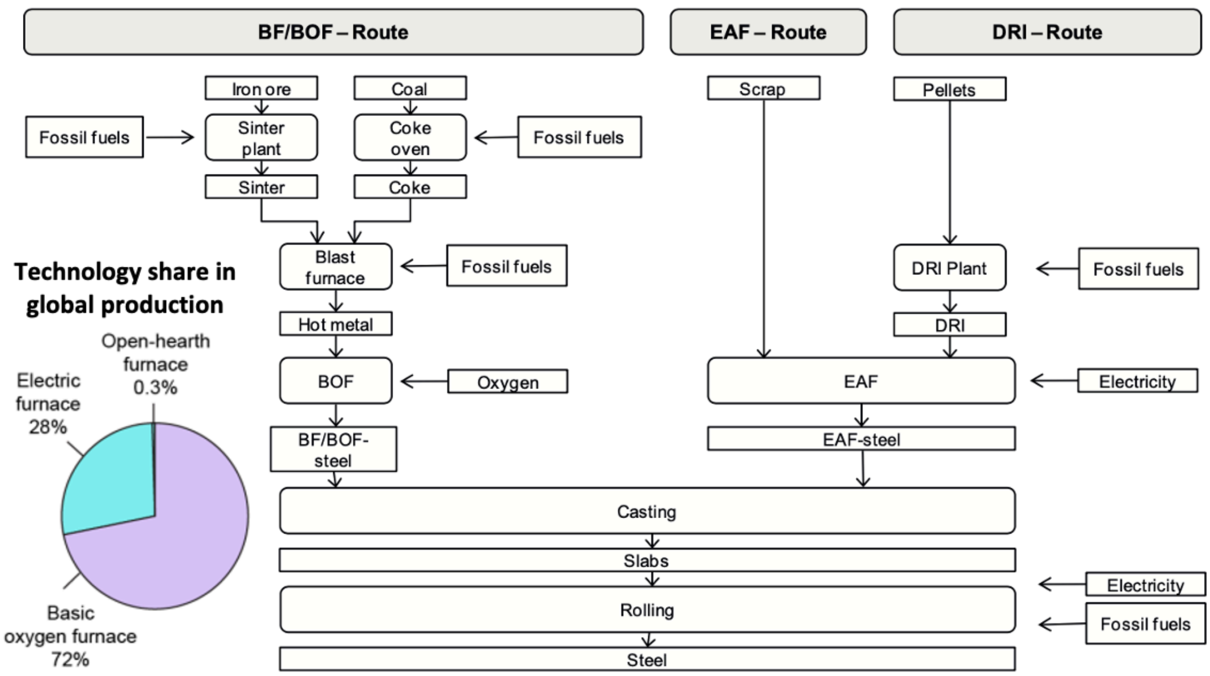


Traditionally, the steel industry has been the largest consumer of energy among industrial sectors (De Beer et al., 1998). Though the industry has seen substantial growth over the last decades, efficiency improvements and absolute growth in especially the chemical sector place the steel industry at a current second place with regards to industrial energy use (IEA, 2020). Altogether the sector consumes 8% of total final energy (IEA, 2020). Moreover, about one-fifth of industrial final energy consumption is used for steel-making, specifically for the deduction of usable iron from iron ore (Banerjee et al., 2012; Arens, 2016). A main reason for this fact is the industry's reliance on coal, which is the most commonly used energy carrier for steel-making at around three-quarters of total energy use (IEA, 2020). However, different steel-making technologies exist and their (potential) reliance on fossil fuels differs substantially.

Current steel-making is most often done using the blast furnace – basic oxygen furnace (BF-BOF) route (Arens, 2016). In the BF-BOF method, iron ore is first transformed into molten iron (i.e. hot metal) in the blast furnace. This process requires temperatures up to 2200℃ and is therefore the most energy-intensive phase of steel production (Arens, 2016). In order to make the resulting hot metal into crude steel, the molten iron is put into a basic oxygen furnace. Oxygen is fed into the furnace – which is heated to 1700℃ – resulting in the oxidisation of the remaining carbon, thereby reducing the material's carbon content and producing steel (Oster, 1982).

The second more common production route for steel utilises the electric arc furnace (EAF). This technology is used considerably less than the BOF (Figure 3.2), but does offer the opportunity to input more scrap metal (100% for EAFs vs. 30% for BOFs; De Beer et al. (1998)). As such, the EAF route is the standard choice for scrap-based (i.e. secondary) steel manufacturing (Arens, 2016; IEA, 2020). As Figure 3.2 shows, apart from scrap metal, EAFs can be fed with direct reduced iron (DRI) made from iron ore pellets. In order to transform the pellets into DRI, either gas or coal is used, often depending on availability and cost (Ramakgala et al., 2019). However, producing steel through the EAF route by replacing these fossil energy carriers with renewable alternatives is a decarbonisation option with large potential (Hoffmann et al., 2020).

Figure 3.2: Depiction of the two main steel-making routes and their share in global production (Source: Arens (2016) and IEA (2020))



3.2 Technological feasibility of low-carbon steel

Reducing the emissions from steel production is possible, but faces a number of challenges. Globally, although the energy-intensity of steel manufacturing has (slightly) decreased in recent decades, this has largely been negated by the growth in total production over the same time period (IEA, 2020). Since the most energy-intensive step of steel production is the transformation of iron ore into usable iron, substantial energy savings – and thereby emission reductions – can be achieved by using secondary (i.e. scrap) metal. More specifically, fully scrap-based steel production consumes a mere one-eight of the final energy primary production needs (IEA, 2020). With current steel stocks reaching their end of life, it is projected that more scrap will become available in the coming decades. Still, considering that the steel demand for many regions will continue to rise, primary production will remain necessary for the foreseeable future (Vogl et al., 2018). As such, it is important to sketch an overview of technologies presently available and under development that may aid the steel sector in its deep decarbonisation. Moreover, to get a comprehensive overview of the factors affecting companies' adoption of pro-climate practices, a number of important drivers and barriers to the adoption of less environmentally impactful production methods are discussed. As literature specific to the steel industry or SBT adoption is often unavailable, these factors are identified by conducting a literature review on the drivers of environmental performance among companies in general. Where possible, the findings are complemented by more specific literature.

Technologies to decarbonise the steel sector

The technologies currently available and under development to reduce GHG emissions from the steel sector differ per production route. In this section, an overview of some of the emission reduction techniques is given.

Regarding the BF-BOF method, the decarbonisation approaches are focused on reducing emissions without the aim of full decarbonisation (Hoffmann et al., 2020). By adopting the currently best available technologies (BATs) and thereby improving the efficiency of steel operations, almost 20% of energy can be saved compared to the current average (IEA, 2020). One important way of doing so is by optimising the use of energy flows. For instance, top-gas can be recycled and re-introduced into the blast furnace iron making process or waste heat can be used for the generation of low-carbon electricity (Nurdiawati et al., 2021; IEA, 2020). Another way in which steel produced via the basic oxygen furnace route can be made less emission-intensive, is by adopting the smelting reduction process. In this method, iron ore is reduced to iron in a smelting unit that does not need carbon-intensive coke as input but could be heated using alternative biomass sources (De Beer et al., 1998; Nurdiawati et al., 2021). Alternatively, or in combination, current BF-BOF capacity can be retrofitted with carbon capture and storage (CCS) technologies. This allows steel companies to maintain production using the predominant route. However, the Global CCS Institute (2017) found that policies and financial incentives are not yet sufficient to motivate steel companies to adopt this technology. Specifically, the institute identified that up until 2017, only one large CCS project (>0.5 Mt per year) was implemented.

Concerning the production of steel by using an EAF, significant emission reductions can be achieved with already proven methods. As discussed in Section 3.1, it is possible to input 100% scrap into an electric arc furnace. This production method would in essence only require the electricity needed to power the EAF, which, if from renewable sources, can be almost emission free. However, access to renewable electricity and high-quality secondary steel are limiting factors (Hoffmann et al., 2020). It is therefore often necessary to mix scrap with DRI, the production of which is an energy-intensive process that currently requires fossil fuels (De Beer et al., 1998; Ramakgala et al., 2019). In order to make this route near zero emissions, the EAF would have to be combined with DRI produced using green H_2 (Hoffmann et al., 2020). Though Nurdiawati et al. (2021) suggest (green) hydrogen-based direct reduction is only at technology readiness level (TRL) 5-7[1], Hoffmann et al. (2020) argue it is available already though at a higher cost than conventional technologies.

A technology that could also be valuable in the long-term electrification of the steel industry but is not yet far developed, is electrowinning. By adopting a combination of electrowinning with EAF, up to 98% of emissions can be reduced compared to current standards (Lopez et al., 2022). Electrowinning could replace other technologies that focus on producing (molten) iron from iron ore, however, is not likely to be widely available before 2040 (Lopez et al., 2022). It therefore seems that a combination of the EAF with green hydrogen-based direct reduction of iron is the most feasible net zero alternative in the coming decades, apart from using more secondary inputs.

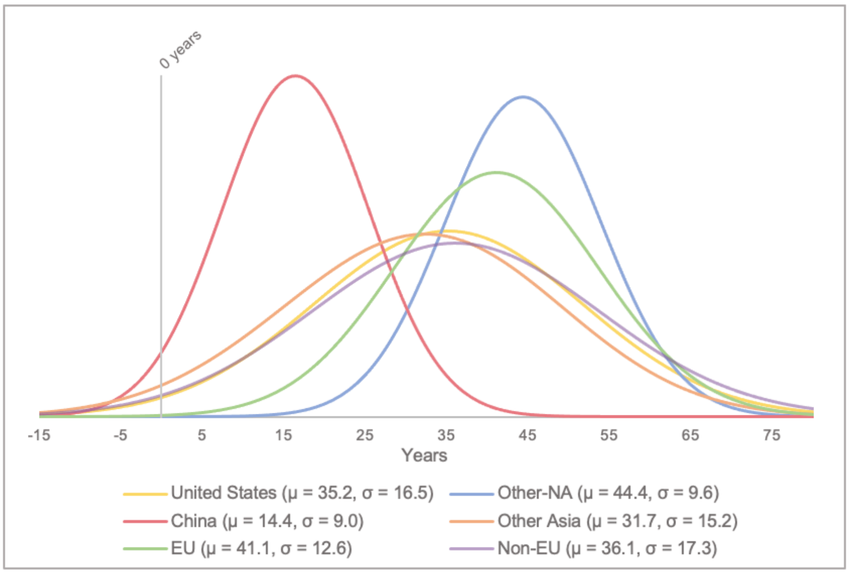
Age of current facilities and technologies

As the previous section outlines, there are technologies available to drastically reduce the GHG emissions from steel production. However, the steel industry is characterised by very long investment cycles to earn back the initial cost of a technology or facility. Vogl et al. (2019) report that large-scale rebuilding opportunities only arise every 15 to 20 years when the technology in a plant needs refurbishment or replacement. The International Energy Agency even reports operational lifetimes up to 40 years, with major maintenance happening some 20 to 25 years after the start of production (IEA, 2022a). Bataille et al. (2021) also take 25 years as the estimated time between building (or past refurbishing) and retrofitting. Acknowledging the substantial length of time that goes by between major decarbonisation opportunities, 2050 (i.e. the net zero year for many regions) is only one investment cycle away and many steel-making plants are locked into carbon-intensive production technologies. The age of a steel plant can thus significantly influence the economic viability of investing in deep decarbonisation (OECD, 2023). Specifically, steel-making assets that have not yet completed one investment cycle are less likely to introduce the large-scale transformations necessary for substantial emission reduction. Contrarily, when reaching their end-of-life, older plants have an opportunity to substitute high-emission assets for more climate friendly alternatives (OECD, 2023). As Hermwille et al. (2022)

[1]Technology Readiness Levels reach from TRL 1 – 'basic principles observed' to TRL 9 – 'actual system proven in operational environment'. TRL 6 suggests that a technology has been demonstrated in a relevant environment (Commission, 2014)

report that approximately half of global steel industry assets need replacement by 2030, there thus exist opportunities for decarbonisation at many plants in the coming years. Worthwhile to note, however, is that when aggregating data from the Global Energy Infrastructure Emissions Database (GID, n.d.), it becomes clear that the age of steel-making capacity differs strongly per region. As Figure 3.3 indicates, steel production assets in the EU and Other-NA are relatively old, with an average age between 40-45 years. While the average capacity in the non-EU, United States and Other Asia has been around for 31-36 years, China's rapid growth in recent decades has led to much new capacity and an average asset age of only 16 years. Concretely, with the phasing out of older technologies in the regions with a higher capacity age (e.g. the EU) and need for refurbishment or maintenance in younger plants, steelmakers will have the opportunity to deeply transform their operations towards decarbonisation. Still, it must be noted that in certain regions (e.g. India) growth of the steel industry is happening in this moment, meaning there will be more capacity added in the coming years. This is not represented in the data and though steelmakers in such regions can opt for low-carbon technologies, substantial growth in demand is often met by increased production via the BF-BOF route (OECD, 2023).

Figure 3.3: Normal distribution of the age of steel-making capacity across regions (Source: based on data from GID (n.d.))



Note: Data is from the Global Energy Infrastructure Database and is aggregated per region using a weighted average and weighted standard deviation with weights based on the amount of capacity with a certain age. To aggregate the data for the studied regions, Other-NA is proxied by Canada only, the EU by 'Western Europe', Non-EU by Russia and 'Eastern Europe' and Other Asia by India and 'East Asia'. Intervals in the database were represented by the average age of the interval (e.g. all capacity in the interval of 0-5 years of age was assumed 2.5 years old) and capacity ages were assumed to follow a normal distribution. Negative ages are in the model treated as the lowest interval (i.e. 2.5 years old).

3.3 Factors that drive environmental performance among firms

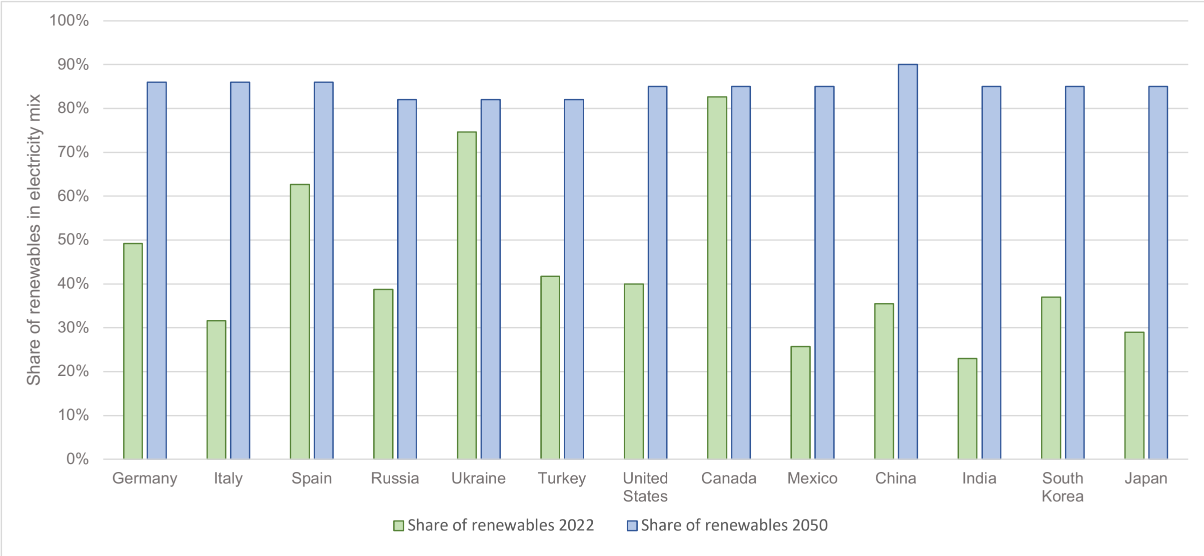
As identified in chapter 1, the need is high for companies to help in keeping climate change to a minimum. Though climate action can be a competitive advantage, carbon pricing poses a financial risk and the consequences of climate change put many company assets at risk, in many industries corporate climate action is not yet the norm (Li et al., 2019). This section focuses on outlining the most important drivers to pro-climate business action. With literature not readily available specific to the steel sector, it is assumed that these drivers are also important for steel-making companies. The drivers are grouped into six categories and are elaborated on below.

Technological considerations regarding company and plant location

The location of a firm is important in a number of ways. As discussed in section 3.2, the age of production assets differs substantially among steel-making regions. However, the age of assets is principal in steelmakers' decisions to invest in low-carbon technologies, considering the assets are long-lived. Moreover, in order to change towards less emission-intensive steel technologies (e.g. EAF and green-H_2), it is imperative that low-carbon electricity is available. When assessing the proxy countries, Figure 3.4 shows that companies in for example Spain, Ukraine and Canada have considerable access to renewable electricity. In other countries, the share of electricity produced using renewable sources is lower, though it is estimated that global expanses in electricity capacity until 2050 will largely be met by renewables (IEA, 2022a). The proportion of electricity available from low-carbon sources is therefore set to increase for all regions. Over time, as the share of renewables expands, more green energy will become available for steelmakers to use in their production process. Consequently, their ability to reduce emissions would also increase, as they would no longer be limited to an electricity mix largely based on fossil fuels.

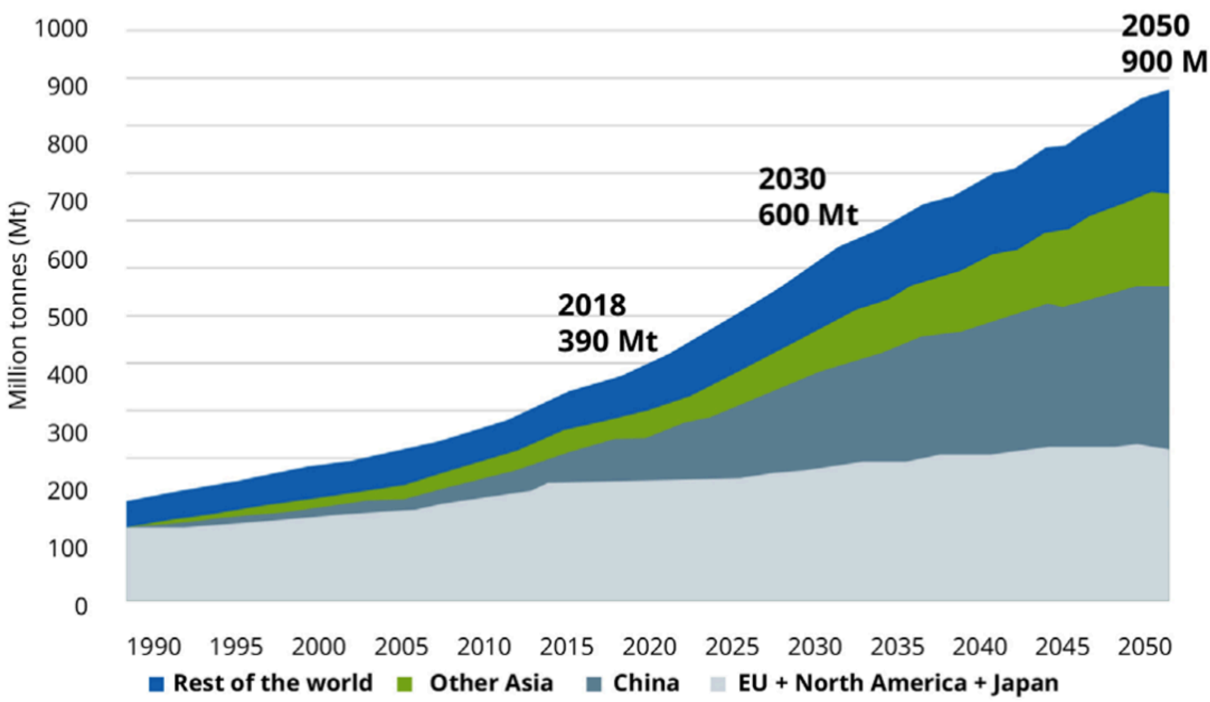
Although the access to low-carbon electricity is important, using scrap as input is likely the most effective way to reduce energy use and GHG emissions. As a projection by WorldSteel (2021a) suggests, the amount of steel scrap available globally is set to increase noticeably. Especially Asia and in particular China will see large increases in the availability of secondary steel, following the economic growth spurt of the region in the last decades (Figure 3.5). Considering the circularity potential of steel, as is also recognised by the Science Based Targets initiative (see Chapter 4), the potential of production using scrap is an important determinant in reducing emissions from steel-making.

Figure 3.4: Share of electricity generation using low-carbon sources for the different regions (Source: LowCarbonPower (n.d.) and IRENA (2020))



Note: 2050 values from the IRENA Transforming Energy Scenario. Specifically, Non-EU countries were proxied by 'Rest of Europe', United States and Other-NA countries by 'North America', China by 'East Asia' and Other Asian countries by 'South East Asia'.

Figure 3.5: Expected end-of-life availability of scrap steel (Source: WorldSteel (2021a))



Financial performance and externalities pricing

A company's financial position to a large extent determines the amount of risk it is willing to take and to which extent it is willing to invest in – possibly more expensive – decarbonisation options. Arens et al. (2017) note, for example, that the payback period of companies' investments is an important driver of the adoption of less energy-intensive assets. More concretely, the authors note that too long payback periods strongly inhibit most companies' willingness to invest in energy efficient technologies. Similarly, it is suggested that firms only focus on novel low-carbon production technologies when significant capital is available. Consequently, a lack thereof puts a company in a position where it is not able or willing to commit to decarbonisation (Arens et al., 2017). This is further substantiated by Singal (2014), who suggests that firms that perform well financially in general do better when it concerns the adoption of environmental action. Earnhart et al. (2006) come to a similar conclusion in that they find that financial success is positively linked with a firm's environmental performance in the future. Thereby the authors suggest that financially well performing firms have more liquidity, allowing them to invest in activities that reduce the respective firm's emissions.

Another financial aspect considered by companies is carbon pricing. Though it is uncertain from which carbon price level it will become beneficial for companies to adopt low-carbon technologies, Hoffmann et al. (2020) argue that carbon prices of €55-€95/ton[2] could already be enough for businesses based in Germany. Currently, the cap-and-trade system of the European Union (i.e. the EU-ETS) already sells carbon emissions allowances within this price range (Ember, n.d.). On top of EU carbon pricing, of the proxy countries covered in this study, China, South Korea and Canada have in some way incorporated a carbon price for steel production (Worldbank, n.d.). More specifically, the Canadian carbon tax will increase to above €55/ton in 2024, while experts project that also in China and South Korea carbon allowance trading will result in prices above €40/ton and €50/ton, respectively, by the end of the decade (IETA, 2022). Taking this into account, it is hypothesised that carbon pricing will be a significant driver of corporate climate action. Though the steel industry is currently largely exempt from this financial mechanism, it will become more exposed to emissions pricing in the coming decade (see Appendix A.5 for more elaboration).

The decision-making body

In the end, the decision to take company-wide environmental action is taken by the board of directors of large organisations. However, of whom the board consists and to what extent directors favour corporate climate action differs per company.

[2]Note, a ton here refers to a ton in emitted greenhouse gas emissions in CO_2-equivalent.

Ownership

A first important factor to consider is the ownership of a company. Steelmakers are considered to be either state-owned (i.e. control lies for the majority with the government of the country where the company has its headquarters), publicly listed (i.e. their ownership shares are traded on the stock market and the majority of its shares are not owned by one entity) or private (i.e. a wealthy family or individual owns a majority share of the company's ownership). In what direction and to what extent ownership affects a business' environmental efforts varies considerably depending for example on where the company is from.

Earnhart et al. (2006) suggest that it is beneficial if the state owns the majority share of a company, as state-owned entities outperform the other types of ownership concerning environmental performance. Similar conclusions are drawn by Calza et al. (2016), who infer that when companies are owned by the state, they are more proactive when it comes to taking environmental action. However, both these studies were conducted using a sample of European firms, limiting the generalisability of their findings to companies in other regions. Contrarily, Wang et al. (2007), find that state-owned companies in China have lower levels of environmental performance than their listed and private counterparts. If state ownership is thus a driver or barrier to climate action depends largely on the state in charge.

Similar arguments are made regarding publicly listed firms. According to Dyck et al. (2019), institutional investors focus on increasing the environmental performance of the companies they own, if the investors are from regions where sustainability is regarded as relatively important. The authors find that while European investors push for climate action, there is no significant effect on environmental performance if the investors are from North America or Asia. While not focusing on the geographical location of institutional investors, Kordsachia et al. (2021) further substantiate these findings by showing that if a firm has sustainability oriented investors, it performs better environmentally.

Regarding private firms, literature implies that this form of ownership is not positively associated with environmental action. Dekker et al. (2016) conclude that private companies do not perform better regarding environmental performance compared to publicly listed or state-owned firms. On the contrary, they suggest that private firms actually perform worse. This could be explained by the fact that private firms likely have fewer independent directors, the number of which has been found to be positively related to environmental action (De Villiers et al., 2011). Moreover, private companies owned by families are also believed to be less environment focused in their values compared to entities with other forms of ownership (Craig et al., 2006).

The board

Apart from the ownership dimension, literature shows that a number board-related characteristics influence a company's stance towards environmental action. Firstly, the size of the board (i.e. the number of directors on the board) is positively related to climate action. Galbreath (2010) shows that boards with more members are associated with more pro-climate governance practices. Additionally, when boards consist of more directors, there is a higher chance that the total expertise of board members meets the level necessary for adequate corporate environmental performance (De Villiers et al., 2011).

Secondly, the age of directors is negatively associated with environmental performance among companies. This is likely due the constantly changing business environment, which requires innovativeness and flexibility that characterise younger directors (Galbreath, 2010).

A last important feature of corporate boards when considering companies' focus on environmental action is the diversity of the board. Diversity can take shape in many forms, but Kizys et al. (2023) argue that especially genetic diversity among board members is important. The authors posit that increases in a board's genetic diversity improve a company's environmental disclosure practices, reduces its relative carbon emissions and increases environmental performance. Moreover, higher gender diversity in boards can result in more renewable energy use (Zhang et al., 2021), while simultaneously having a positive effect on corporate carbon and corporate environmental performance (Kizys et al., 2023). Altogether, diverse boards are believed to more adequately possess the expertise necessary for corporate environmental action than non-diverse boards (De Villiers et al., 2011).

Contextual factors

On top of the ownership and corporate board dimensions of the decision-making process, there are a number of contextual factors important for companies that have not yet been mentioned. Specifically, companies always exist within a sector. As such they compete and cooperate with other firms. The actions of other steelmakers are therefore hypothesised to influence the behaviour of a steel company. To what extent a company values other firms' decisions depends on cultural factors such as if a company is individualistic or collectivistic. Moreover, a steel company's activities may be subject to stakeholder pressure, as steel-making operations result in substantial negative externalities. The countries studied in this work have strongly varying contexts that for example influence to what extent companies perceive the behaviour of others as important, stakeholders pressure firms to reduce their emissions and steelmakers are focused on the long term.

Company size

As explained above, diversity and board size are important drivers of businesses' environmental performance. Important in determining the diversity and size of corporate boards, however, is the size of the respective company. As Arnegger et al. (2014) point out, the diversity of a firm's board is substantially influenced by that firm's size. Moreover, since larger companies have more relationships with external contractors and a higher advisory need, they often also have boards comprising of more directors (Coles et al., 2008; Guest, 2008). Concretely, the larger the company, the larger its board (Boone et al., 2007).

Yet board diversity and size are not the only two important aspects influenced by a company's size. Frequently, larger companies are more visible to the public for scrutiny and are therefore under pressure from a broader range of stakeholders (Bowen, 2002). When faced with such pressures, larger firms often use their resources for resistance efforts rather than changing their business practices. Smaller companies, however, may receive stakeholder pressure less often, but are more responsive to it in their actions (Bowen, 2002). Altogether, larger companies thus take more gradual environmental action because they are more often exposed to stakeholder pressure, while smaller firms respond with more vigour in the rarer case that they are (Darnall et al., 2010).

3.4 Conclusion

This chapter discusses the findings of a literature analysis that was conducted with a focus on the steel industry to answer sub-question I: **Which company and environmental characteristics are important for companies in their decision-making procedure regarding target-based climate action?**

Altogether it can be concluded that a number of options exist through which the steel industry can deeply decarbonise. However, the economic viability of these differs substantially. In order to take these options into account, the ABM should incorporate important limiting factors such as the availability of scrap and renewable energy. Moreover, even if such factors are available, companies will assess if there are decarbonisation opportunities for their production capacity in the coming years. Only when a company perceives decarbonisation as an economically worthwhile endeavour, it will consider increasing its climate action. Forces that play on this are internal - primarily financial liquidity - and external - mostly carbon pricing. At last, decisions regarding climate action will be made by a company's corporate board. A number of factors such as the board's diversity, size and average age determine to what extent a board is open to consider pursuing decarbonisation efforts. In doing so, they are hypothesised to be influenced by the wider cultural context, the pressure exerted by stakeholder groups as well as the behaviour of other firms in the industry.

Chapter 4

Science Based Targets and the SBTi

4.1 Science-based targets to reduce emissions

In order to limit the strongest effects of global climate change, science-based targets align companies' ambitions for emission reduction with the latest climate science (Bjørn et al., 2022). The translation of the global challenge to mitigate climate change into company-level goals has been hailed as a catalyst for change with the potential to positively influence international policy and reduction targets (Marland et al., 2015; Lister, 2018). However, opponents of the methodology suggest that SBTs could unintentionally delay and weaken global pro-climate efforts by signalling that private action could substitute public policy (Trexler et al., 2015). Similarly, Trexler et al. (2015) believed at the launch of the SBTi that only few businesses would actually set science-based targets.

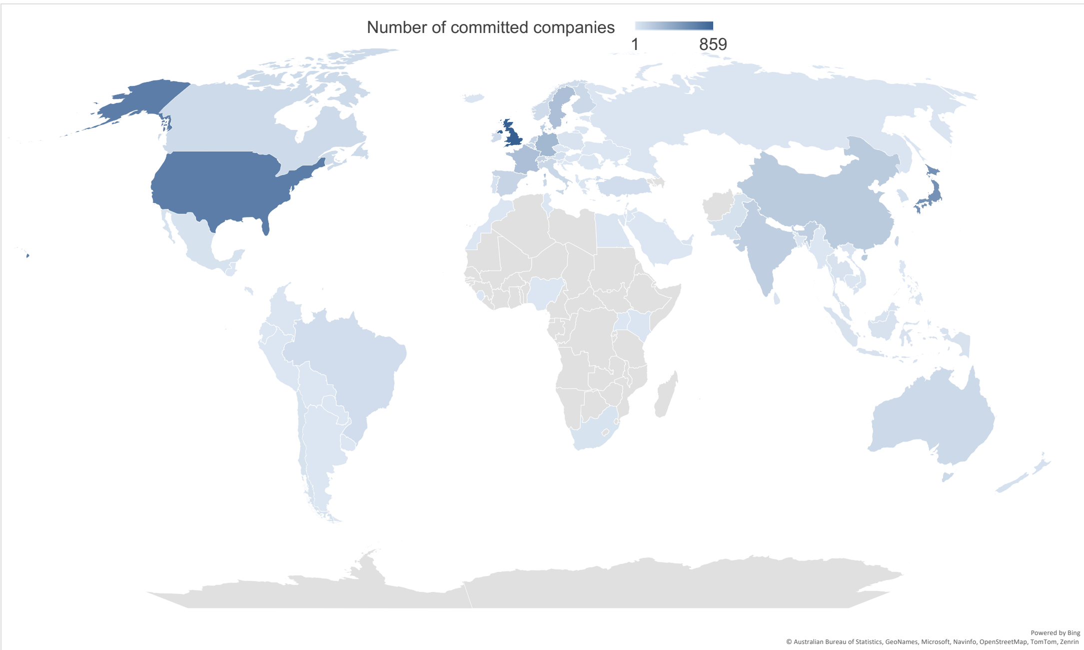
Though it has become clear that there are many companies who have or consider setting SBTs, there is still ambiguity surrounding the actual impact of this climate mitigation effort. To successfully reach the temperature limit as set out by the Paris Agreement, global collaborative effort is needed. Presently, however, companies in lower income regions and certain sectors are unevenly represented, with exactly those companies committing to SBTs that are already more environmentally motivated (Bjørn et al., 2022; Giesekam et al., 2021).

Still, initiatives such as the SBTi believe that initial adopters could stimulate sector-wide diffusion, while Banda (2018) suggests pro-climate companies can influence other businesses through normative and market pressures. Correspondingly, Freiberg et al. (2021) note that setting SBTs does not entail that companies' reduction targets get more ambitious, but it does lead to more financial backing of emission reduction efforts. In line with that, Höhne et al. (2021) argue that science-based targets have the potential to align international decarbonisation efforts with a 2℃ temperature limit. In order to adequately reduce global emissions, however, it is imperative that more market actors align their net zero trajectories with the latest climate change research.

4.2 Introduction and role of the SBTi

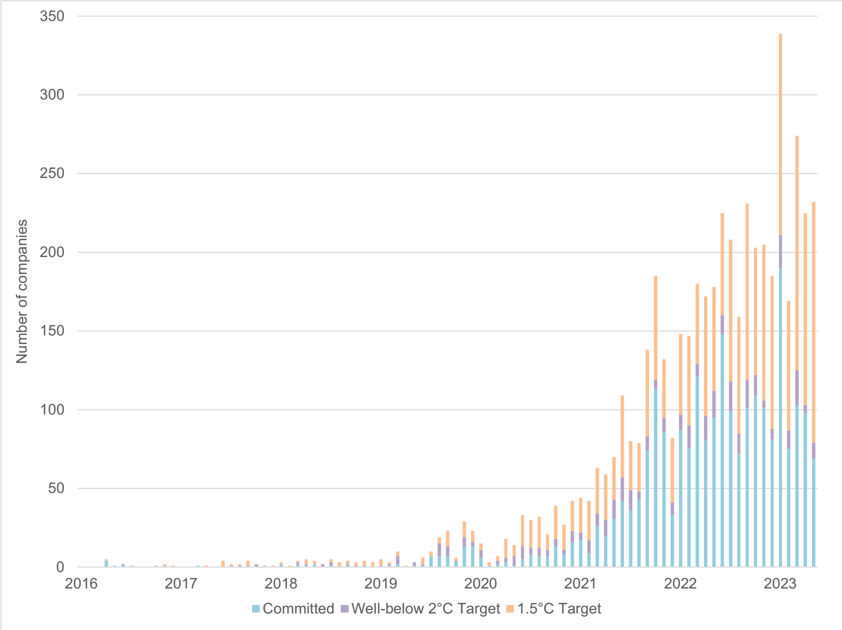
The Science Based Targets initiative is a collaborative effort that focuses on reducing the climate impact of companies. The initiative was launched in 2015 by UN Global Compact, CDP, WWF and the World Resources Institute to aid businesses in setting research based emission reduction targets. As was established in Chapter 1, most companies that have set SBTs validated by the SBTi are European. At the time of writing, however, the SBTi has already attracted 5172 organisations to commit to target setting, of which more than half have approved SBTs. Setting targets following the SBTi's frameworks is gaining more and more momentum (Figure 4.2) and though European companies are front runners, businesses on other continents are also increasingly committing (Figure 4.1).

Figure 4.1: Global diffusion of targets validated by the SBTi (Source: data from SBTi (n.d.[b]))



Note: Grey areas have no companies with SBTs from the SBTi or commitments to set SBTi validated targets. The total number of committed companies in the three regions studied are: Europe – 5428, North America – 774 and Asia – 1410 on 24/06/2023.

Figure 4.2: Number of companies committing or setting targets per month since January 2016 (Source: data from SBTi (n.d.[b]))

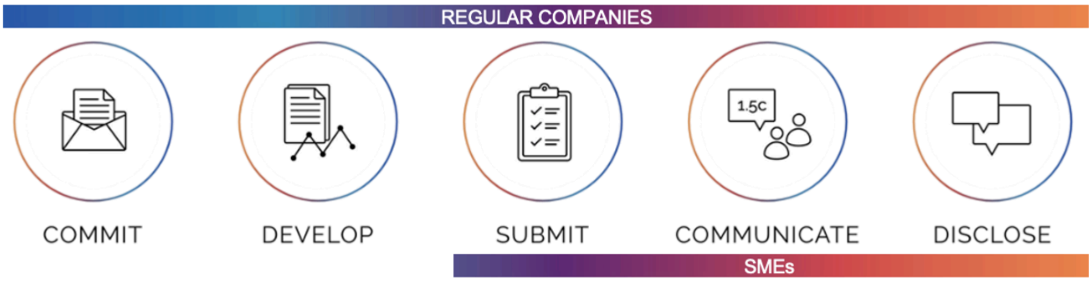


For a number of sectors, the SBTi releases sector-specific pathways and tools to aid the target setting process. Steel is one of these sectors and the initiative is currently in the middle of developing its guidance documents for this high emission industry (B. Chan, 2022). Specifically, as steel-making has a high potential for circularity and emission reduction through the use of scrap, two different pathways are developed for the sector. In doing so, the SBTi recognises the importance and potential of utilising secondary steel in a circular fashion. Depending on the current and projected availability of steel scrap, each company will therefore have different targets (SBTi, 2022b).

The target setting process

In order to have SBTi validated targets, companies must go through five phases (Figure 4.3). Initially, a company has to communicate to the initiative that it is willing to develop SBTs. In doing so, the business commits itself to setting science-based targets. Afterwards, the entity has a period of 24 months to develop emission reduction targets using the criteria set out by the SBTi. These preliminary targets are submitted to and assessed by the SBTi to ensure they are aligned with what the academic consensus on climate change deems necessary action. If approved, stakeholders are informed of the set targets and the company is required to disclose annual emissions and progress to the public (SBTi, n.d.[a]).

Figure 4.3: Steps towards SBTi certified targets (Source: adapted from SBTi (n.d.[a]))



In order for the targets of committed companies to be comparable, the SBTi utilises a number of criteria regarding target setting (SBTi, 2023). The initiative encourages parent companies to set targets, which in turn should include all the emissions from the subsidiary level. The reduction goals must include all GHG emissions - not merely carbon dioxide - in scope 1 and 2 of the company. Additionally an entity is required to incorporate its scope 3 emissions into its near-term SBTs if these emissions make up 40% or more of that company's total emissions (scope 1, 2 and 3). Companies are thus encouraged to engage with up- and downstream players to reduce the overall emissions of their operations and products. Moreover, firms in the process of target setting must develop engagement goals that in essence determine that suppliers and customers should also develop SBTs. For the near-term scope 1 and 2 targets, businesses are required to be ambitious and align their SBTs with the degree of decarbonisation necessary to limit temperature rise to 1.5℃. As was mentioned before, the SBTi has developed a number of sector specific decarbonisation pathways (i.e. Sectoral Decarbonisation Approaches), among which there is an approach for the steel sector. Taking into account the contextual factors of the sector, this pathway guides steel-making companies towards a level of decarbonisation that is in line with 1.5℃. More generally, companies also have an alternative to reducing their scope 2 reduction targets, which is by setting renewable electricity sourcing goals. Regarding scope 3 emission reduction, companies should at least align their objectives with a temperature increase pathway well-below 2℃.

To maintain alignment with the latest climate science and industry standards, it is required to periodically review, and potentially re-align, SBTs at least once every five years. On top of that, targets must be recalculated and validated in the case that there are changes compromising the existing objectives. Examples of such changes include scope 3 emissions newly accounting for 40% or more of total emissions or substantial changes to a company's activities following a merger or acquisition (SBTi, 2023).

4.3 Engagement strategies (levers) of the SBTi

For the SBTi to be most successful in attracting new companies to set SBTs, the initiative utilises a number of so-called engagement strategies. Generally, the SBTi adopts an approach focused on direct engagement with companies, prioritising collaboration with corporate entities rather than governmental bodies (Khan et al., 2023). A dedicated corporate engagement team actively participates in sector-related events, raising awareness about the SBTi and encouraging companies to adopt science-based targets. Additionally, the SBTi utilises webinars as a means to engage and update a wider range of stakeholders on the progress and developments within their steel decarbonisation project (Khan et al., 2023).

To ensure diverse perspectives and the dissemination of relevant information, the SBTi has established Expert Advisory Groups (EAGs) specific to each high-impact sector. These EAGs consist of representatives from various entities, including companies, NGOs, and academia, contributing valuable input and acting as channels for distributing information through their networks.

Furthermore, the SBTi actively targets companies that already disclose their data to the CDP, recognising the significance of existing sustainability efforts. In particular, the initiative runs a campaign with CDP to stimulate SBTi commitment through supply chain engagement (CDP, 2022a). Moreover, the campaign involves investors who seek to make their portfolios more environmentally responsible. Such investors are motivated to compel their investees to set science aligned emission reduction targets with the SBTi (Khan et al., 2023).

Generally, the SBTi tries to stimulate certain high-impact companies to commit to reducing their emissions. To broaden the initiative's geographical reach, the development of a region-specific engagement approach is prioritised, in which unique local contexts and requirements are addressed (Khan et al., 2023).

4.4 Conclusion

An analysis of the current operations of the Science Based Targets initiative was performed to formulate an answer to the second sub-question: **How does the SBTi currently motivate companies to commit to science-based emission reduction targets through its operations?**

In conclusion, the SBTi is a globally active cooperative initiative with the aim to decarbonise the business sector. The organisation does this by stimulating companies to set science-based emission reduction targets using their guidelines and validation. For the most impactful sectors, the SBTi develops specific decarbonisation pathways. Steel is one such industry and the initiative has developed two pathways that companies can pursue, depending on the availability of secondary steel inputs. In order to raise awareness and gather as many commitments as possible, specific company engagement teams participate in events where the steel companies get together. Moreover, the SBTi works together with CDP on a campaign that mobilises companies through their supply chain and financiers. In all their activities, the initiative takes a local approach and focuses on the most impactful companies.

Chapter 5

Conceptualisation and formalisation of the agent-based model

This chapter outlines and describes the agent-based model that will be used to develop an answer to sub question 3. Agent decision-making in the model follows the logic of the Theory of Planned Behaviour, as was elaborated on in Section 2.4. In the last chapters, a number of factors that are important for steel companies in their decision-making were discussed. This chapter explains how these factors are incorporated in the model and later on in what way the model will be used to simulate scenarios.

In order to give structure to the model description, this chapter loosely follows the reporting approach of Van Dam et al. (2012). For a full and more detailed account of all relevant aspects of the ABM - including the used data - please refer to the complete model description that follows the ODD protocol of Grimm et al. (2020) in Appendix A.

5.1 Conceptual model

Agents and their environment

From the previous chapters, it has become clear that this study focuses on the potential SBT adoption process of some of the largest steel producers. As was explained in Section 1.3, the modelled agents are only steel companies. Specifically the studied population of companies includes two groups, (i) the 113 largest steel producers globally in 2021 and (ii) the present members of WorldSteel that do not fall in the first category. However, companies which fall within one of the abovementioned groups but have headquarters outside of the geographical scope of this study were excluded (see Appendix E for an overview of the included companies).

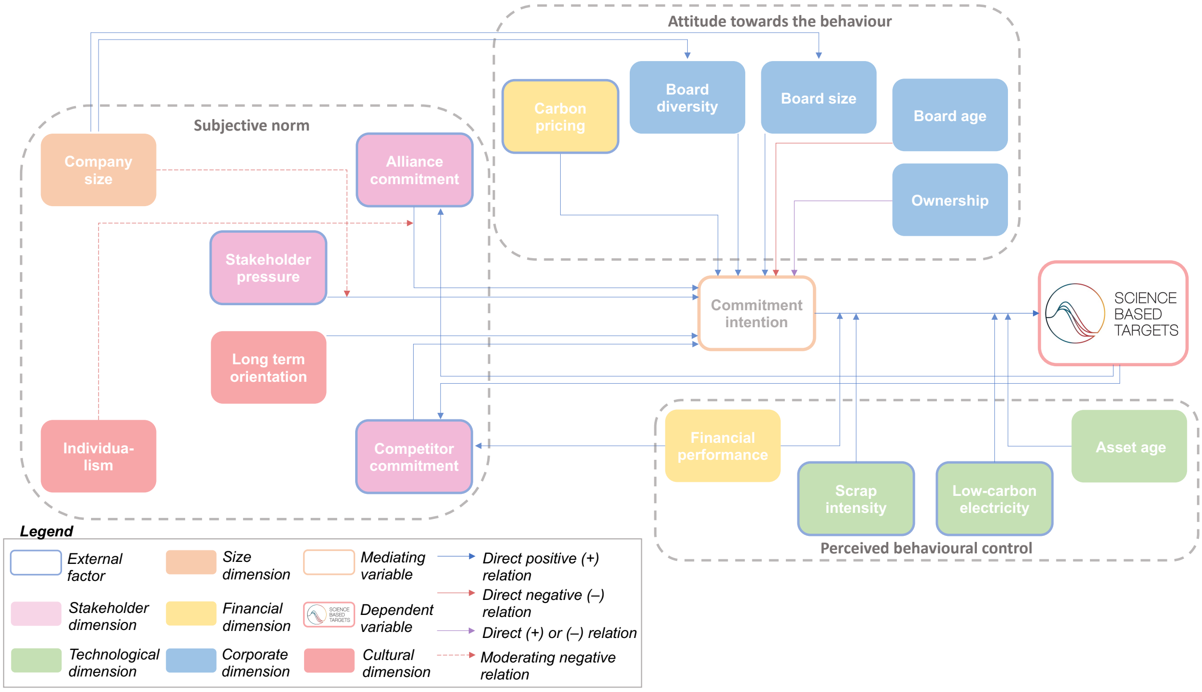
The location of companies is incorporated through three parameters: *country*, *region* and *continent*. As was explained in Section 1.3, this study builds on the use of proxy countries. All incorporated companies that do not have their headquarters in one of these nations are assigned a proxy country on their continent (for a more detailed explanation, please see Appendix A.2). Moreover, to more accurately represent the global nature of many of the included companies, some of the largest steel producers have been split into a number of smaller entities (Appendix A.2). A final number of 163 steelmakers are then modelled. In the model, the companies are connected in a random network, where each company is asked to build a link with a number of other companies (two by default). This specific network configuration is modelled to include the linkages which steel companies are assumed to have in the real world[1]. Connected companies are said to share an alliance. Ojode (2004) argues that such horizontal alliances (i.e. between two or more steel-making companies) can prompt competitive rivalry and lead to the diffusing of best practices in a sector. By including linkages between steelmakers, the effect of alliances on the diffusion of behaviour (see Equation (5.15)) can thus be incorporated in the model. Resulting from the way in which the links are created, companies will often not have the same number of links, though all companies will have at least one link[2].

As was outlined in Chapter 3, there are a number of important determinants for companies' climate action efforts. Building on the Theory of Planned Behaviour and Chapter 3, these hypothesised drivers and inhibitors of target adoption influence the decision-making process as depicted in Figure 5.1. The main state variable of the modelled companies is *Commitment_status* (visualised as the dependent variable in Figure 5.1), which signals if a company has already committed to setting science-based targets. Consequently, this variable determines if a company's decision-making process is activated in a step. Each step represents a period of two weeks with a year consisting of 48 weeks. The model runs for 13 years from the beginning of 2023 until the end of 2035. This time-frame has been chosen as it allows to simulate and study different scenarios, while limiting the uncertainty that comes with longer time horizons in models (Taberna et al., 2020). In line with the argumentation of Arvitrida et al. (2017), companies have the opportunity to commit every board meeting (Table A.1). Specifically, the authors argue that when modelling company decision-making behaviour, the chosen time unit should adequately represent the time needed for an organisation to alter its strategy. As company strategy is often discussed in board meetings, the mean number of board meetings per country is used to initiate agent decision-making behaviour.

[1]Nippon Steel, for example, has developed a number of alliances with other steelmakers over the last years (Nippon Steel, n.d.). However, due to time limitations it was not possible to include all real world company connections.

[2]Note: the variable *Create_links* defines how many linkages each company is asked to create with other steelmakers (randomly). If this variable is set to 0, the logical result is that there will be no linkages.

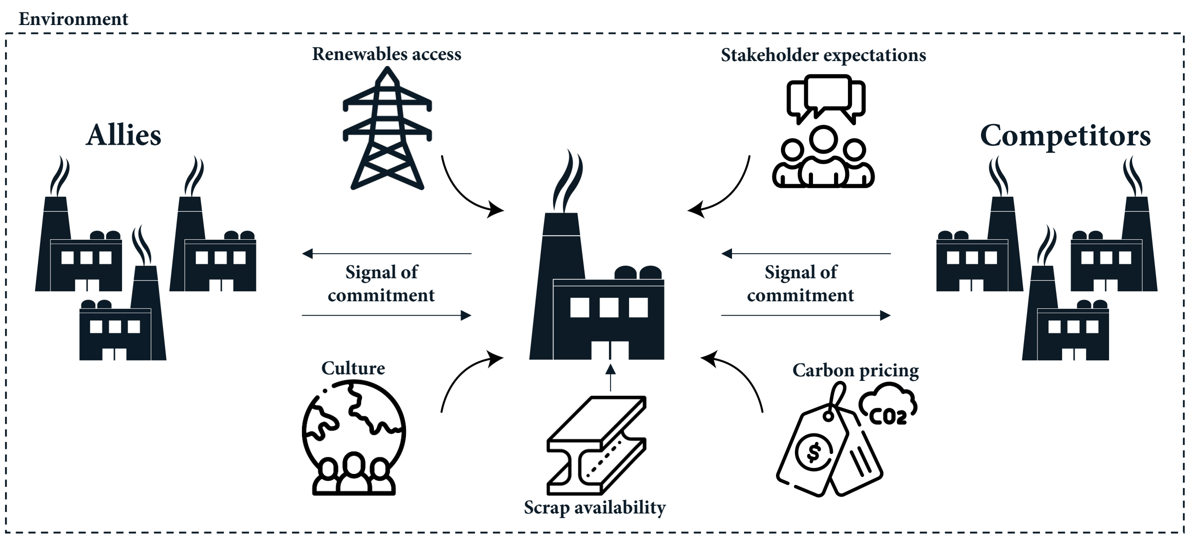
Figure 5.1: Schematic overview of the most important model variables, parameters and relations



Agent interactions

The entities interacting in the model are agents – as steelmakers, competitors and allies – and the environment. The ways in which they interact are depicted in Figure 5.2 and elaborated on below.

Figure 5.2: Simplified overview of the most relevant interactions in the model



Interaction between a steel company and its competitors

Every steelmaker operates in one of the three covered continents (i.e. North America, Europe and Asia). Based on the continent of location, steel companies compete with each other. A steelmaker in Germany is thus assumed to compete with other firms from Germany, Spain and Italy, but not with steel companies from for example South Korea or Canada.

At the moment a company commits to science-based targets, it sends a signal to the other steelmakers on the same continent that commitment is becoming more common in the sector. Competing firms will acknowledge this information, assess what their competitors are doing in general and feel some pressure to also act. Of course this works both ways. If no competitors are committing, a steel company will feel less pressure to commit itself.

Interaction between a steel company and its allies

Similar to the interaction between a steelmaker and its competitors, steel companies care about the activities of their allies. As has been mentioned, in the model agents are linked in a random network to form global alliances. When a company in such an alliance commits to SBTs, it notifies the other alliance members that setting SBTs is becoming more widespread.

Still, the extent to which a steelmaker considers its allies' SBT-related actions as relevant, is dependent on the level of individualism of that company. Individualism is one of the Hofstede (2001) cultural dimensions, which encompasses the degree of loyalty and interdependence between members of an 'in group' (i.e. the alliance). In the case that a company scores high on this dimension, it is 'individualistic' and will value less what its allies are doing regarding SBT adoption. If a company has a high score, however, it is more collectivistic and will be more strongly motivated to mimic the other members in its alliance.

Interaction between a steel company and its environment

Apart from interacting with other agents, the behaviour of modelled steel companies is determined by some financial and technological environmental factors.

Through the pricing of carbon, steelmakers are incentivised to reduce their GHG emissions and potentially commit to SBTs. Of the proxy countries studied in this project, only China, South Korea, Canada and the EU countries have a carbon price that covers the steel industry. All these countries excluding Canada utilise an emissions-trading-scheme, while Canada uses a carbon tax. Considering that not all covered countries currently have a carbon price, the pressure from carbon pricing is assumed zero over the time horizon of the model for the companies in countries where emitting GHGs is free (for the steel industry). It should be acknowledged that some countries with currently no carbon price have plans to establish an ETS or tax, but due to the great uncertainty of timescales, coverage and future price levels such potential plans were excluded from analysis (for elaboration, see Appendix A.5).

Additionally, it is noteworthy that at present a lot of emission rights are allocated for free to companies in the steel sector. This is incorporated in the model by making a distinction between the market carbon price (*Carbon_price*) and the perceived carbon price (*Perceived_price*) by incorporating the share of free allowances (*Free_allowances*). Moreover, in order to standardise the pressure from carbon pricing, it was assumed that a value equal to or over 95 (€) for *Perceived_price* corresponds to maximum pressure. The €95 threshold was taken from Hoffmann et al. (2020), who argue that a carbon price between €55 and €95 is enough to make green hydrogen less costly than grey hydrogen (depending on the electricity price). As the authors base their estimate on Germany, however, the most conservative value in the given range was taken to determine what value for *Perceived_price* should constitute the max value for *Price_pressure*.

Another influential environment-dependent factor is the availability of steel scrap for production. However, although steel scrap can be recycled, it is not only the amount available that should be considered. Rather, as steel production is also estimated to increase over the course of the model, the intensity (i.e. share of scrap in total production) is assessed. Appendix A.5 provides a more in detail explanation of how the scrap intensity is determined and projected to develop.

Finally, as was established in Chapter 3, it is worthwhile to consider the proportion of economic activities that could be conducted using low-carbon electricity. Therefore, it has been analysed what part of country-level electricity generation is done using renewables and is expected to be achieved in the future. Again, please refer to Appendix A.5 for more elaboration.

Parameter overview

In their decision-making process, companies use a broad range of different data and information. To better understand the next section, Table 5.1 and Table 5.2 outline the most important agent and model parameters. A more extensive overview is given in Figure D.1 and Figure D.2 in Appendix D, while a full outline and description of all modelled parameters and variables is available in the supplementary Netlogo model.

Table 5.1: Overview of a few of the most relevant model parameters.

See Appendix D for more of the most relevant company-specific model parameters

Parameter/variable	**Type**	**Value [range]**	**Description**
long_term_threshold	float	[0; 100]	Main threshold used by companies in their decision-making
hof_long	float	[0; 100]	Company score for Hofstede's long term orientation dimension
ownership_pressure	float	[0; 100]	Represents the pressure owners exert on a company to commit
ownership_mp	float	[0; 1]	Multiplier incorporating a company's ownership and environmental performance
perceived_price	float	[0; ∞]	Price of GHG emissions after incorporating freely received allowances
price_pressure	float	[0; 100]	Pressure exerted by carbon pricing towards commitment
share_female	float	[0; 100]	Share of board that is female
board_diversity	float	[0; 100]	Represents how diverse the board is
board_age_pressure	float	[0; 100]	A company's score relating to *board_age* that counts towards 'attitude'
board_size_pressure	float	[0; 100]	A company's score relating to *board_size* that counts towards 'attitude'
stakeholder_pressure	float	[0; 100]	Pressure exerted by general stakeholders towards commitment
scrap_intensity	float	[0; 100]	Estimated share of production possible using scrap input
renew_electricity	float	[0; 100]	Initial share of relevant electricity mix that is renewable

Table 5.2: Overview of a few of the most relevant model parameters

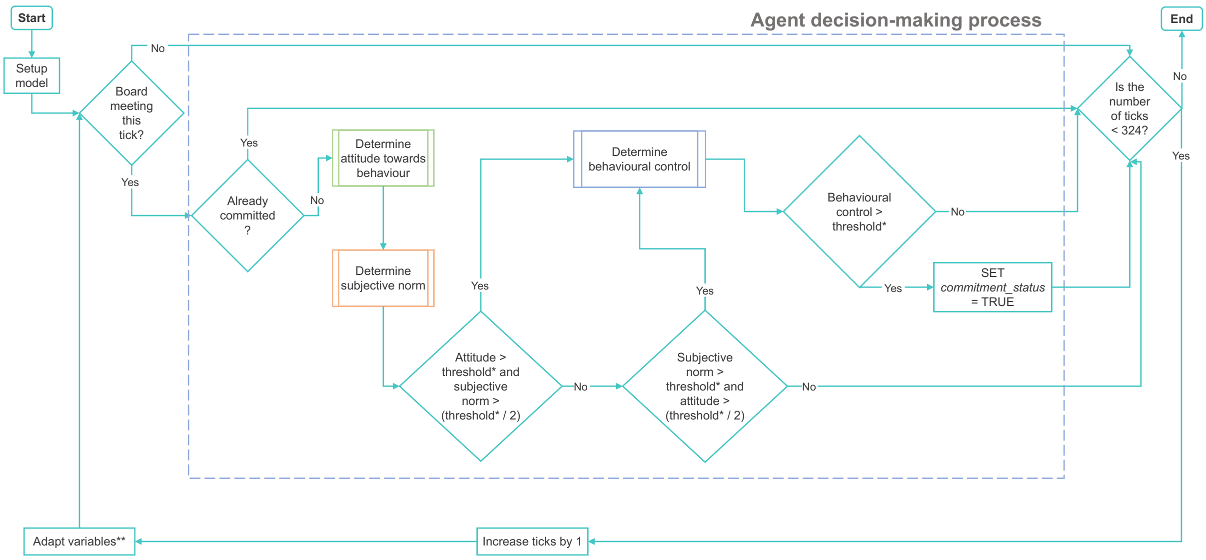
See Appendix D for more of the most relevant model-specific model parameters.

Parameter/variable	**Type**	**Value [range]**	**Description**
standard_threshold	integer	38	Base threshold used by companies to determine the level of attitude, subjective norm and behavioural control needed before they develop intention and/or translate that intention into actual commitment
threshold_mp	float	0.5	Multiplier used to scale down the effect of a company's long-term orientation on that company's *long_term_threshold*
hof_upper_bound	integer	100	Parameter used to include the maximum value of a Hofstede dimension
carbon_price	float	[0; ∞]	Carbon price in a specific country

Decision rules and company behaviour

As was elaborated on above, companies only make decisions regarding SBT commitment during a meeting of the board of directors. As Figure 5.3 shows, the board during such a meeting first establishes the firm's status with regards to target setting. If a business has not yet committed, the board decides the 'attitude' it holds towards commitment. Additionally, the social pressure exerted on the firm by external stakeholders is discussed.

Figure 5.3: Flowchart of model and decision-making procedure



The Long_term_threshold is used in all three decision-making moments and is based on the Hofstede long-term orientation score of each company (see Equation (5.1)).

***Adapt variables refers to the change in variables other than those specified in one of the sub-model flowcharts (see below), following an increase in ticks.*

When a company has a positive 'attitude' it still only develops 'intention' when it perceives a considerable level of 'subjective norm'. Vice versa, if there is substantial social pressure, a company still needs to develop a moderately positive attitude before it intents to commit. As discussed in Section 2.4 and visualised in Figure 5.1, a company will only act on this 'intention' when it perceives reducing emissions in line with SBTs as achievable. Once this is the case, the company commits. In order to determine if the level of a TPB construct is sufficient, the agent uses the following minimum threshold:

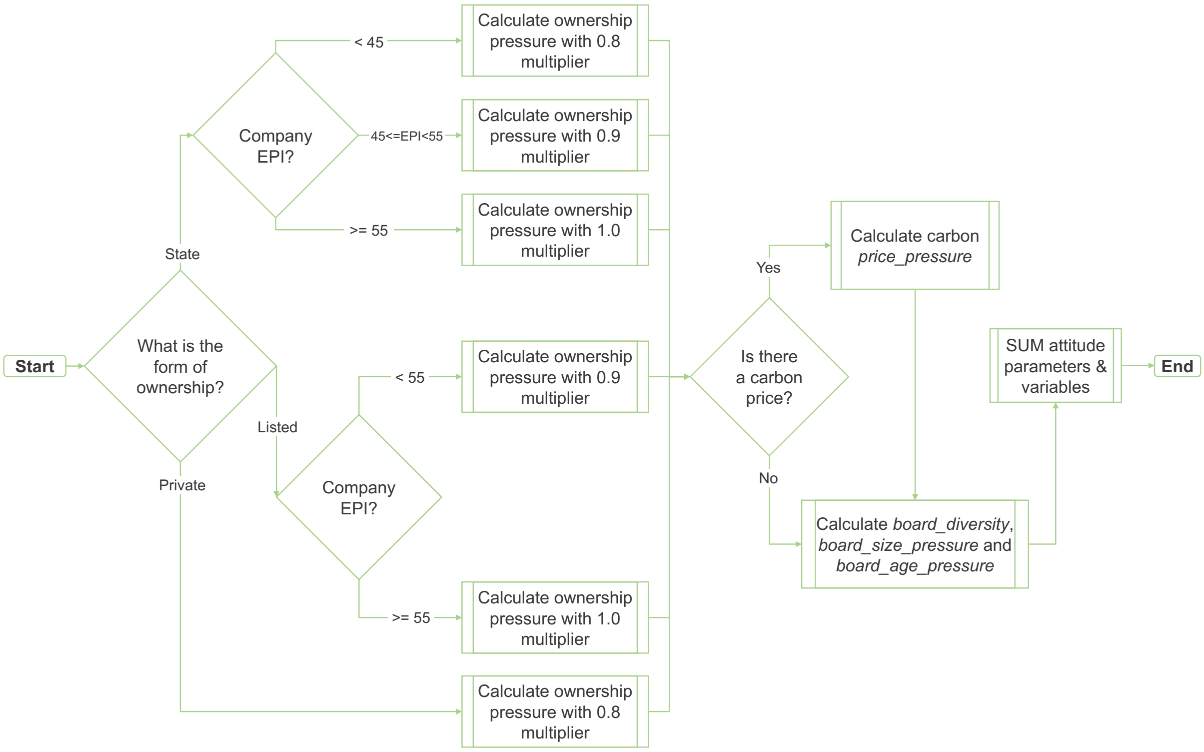
$$Long\_term\_threshold = Standard\_threshold + (Hof\_upper\_bound - Hof\_long) \times Threshold\_mp \quad (5.1)$$

To which extent each company feels social pressure (i.e. 'subjective norm') or holds a positive 'attitude' is mathematically determined following Azjen (2019). More concretely, companies compute a weighted sum of the various factors that influence each TPB construct. Once this weighted sum reaches the *Long_term_threshold* (or in some cases, the *Long_term_threshold* / 2, see Figure 5.3) a company is said to have a positive 'attitude' or substantial 'subjective norm'. How these constructs are exactly determined is discussed in the following sub-sections.

Determining 'attitude'

Non-committed companies start their decision-making process by determining their 'attitude' towards the setting of science-based targets. The process of doing so is outlined in Figure 5.4.

Figure 5.4: Overview of agents' process to determine their attitude towards SBT adoption



First, it is established which type of ownership a company has. Together with the steelmaker's stance towards environmental action - proxied by the Environmental Performance Index (EPI), see Appendix A.5 - this determines the pressure from a company's owners to commit. In other words, the higher a state-owned or listed firm's EPI, the more pressure it will receive from its owners. As was established in Section 3.3, private companies perform worse than most state or listed companies. Consequently, private companies always use a lower multiplier to compute the pressure from owners (*ownership_pressure*):

$$Ownership\_pressure = \frac{Highest\_company\_EPI - Company\_EPI}{Highest\_company\_EPI - Lowest\_company\_EPI} \times Ownership\_mp \times 100 \tag{5.2}$$

After the company has gone through the process of assessing *Ownership_pressure*, it calculates to what extent the current carbon price stimulates SBT adoption. The pressure from carbon pricing is dependent on the share of emission allowances the company receives for free. Moreover, to normalise the computed score between 0-100 the *Price_threshold*[3] is used[4]:

$$Carbon\_price = (Carbon\_price\_slope \times t) + Carbon\_price\_start \tag{5.3}$$

$$Perceived\_price = Carbon\_price \times (1 - Free\_allowances) \tag{5.4}$$

$$Price\_pressure = \frac{Perceived\_price}{Price\_threshold} \times 100 \tag{5.5}$$

Finally, each company incorporates how the features of the board influence the decision-making process. As shown in Figure 5.1, the diversity and size of the board positively influence a company's 'attitude', while older boards are less environmentally proactive. How these variables influence the company's decision-making is calculated as follows:

$$Share\_female = (Share\_female\_slope \times t) + Share\_female\_start \tag{5.6}$$

$$Board\_diversity = Share\_female \times 2 \tag{5.7}$$

$$Board\_size\_pressure = \frac{Board\_size - Board\_size\_min}{Board\_size\_max - Board\_size\_min} \times 100 \tag{5.8}$$

$$Board\_age\_pressure = (1 - (\frac{Board\_age - Board\_age\_min}{Board\_age\_max - Board\_age\_min})) \times 100 \tag{5.9}$$

[3]More concretely, all values for *Perceived_price* equal to or above the *Price_threshold* result in a maximum pressure score of 100. The *Price_threshold* is based on Hoffmann et al. (2020) and elaborated on in Appendix A.

[4]t denotes the current time step with respect to the model start (t=0) in all equations.

The scores for the factors influencing a company's attitude are then summed using weights (Appendix B) to provide the total score for 'attitude' in a specific step:

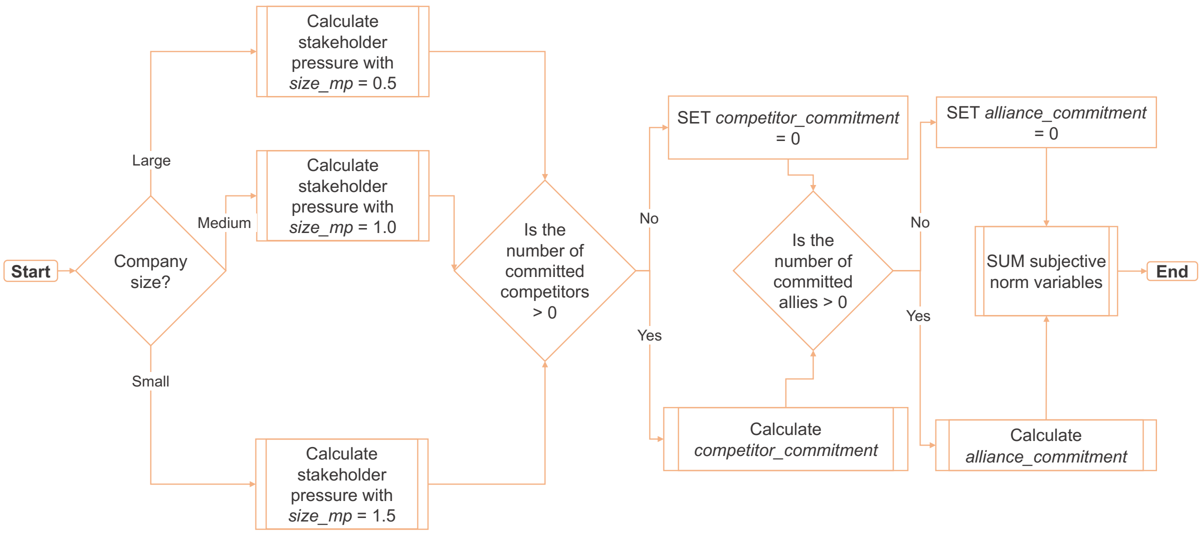
$$Attitude = \sum(Variable\_w \times Variable) \tag{5.10}$$

Where *Variable* represents the different independent variables and parameters directly influencing a company's attitude and *Variable_w* represents the weight given to this specific factor.

Determining 'subjective norm'

In addition to determining the internal attitude of the company towards science-based targets, it is assessed what pressures the company endures from external actors (Figure 5.5).

Figure 5.5: Overview of agents' process to determine the social pressure favouring SBT adoption



Taking into account the reasoning laid out in Section 3.3, that smaller companies respond more vigorously to stakeholder pressure than larger companies, a multiplier is used to incorporate this effect. Moreover, it is included that larger companies are more often subject to stakeholder pressure due to their visibility. The pressure a company then perceives from its stakeholders is also dependent on the country in which it operates. More specifically, it is assumed that high emitting companies - such as steel producers - in environmentally aware countries obtain higher levels of stakeholder pressure. While steelmakers in countries that care less about the environment are likely less subject to pressure from external parties. As with the determination of *Ownership_pressure*, the EPI is used as a proxy for environmental awareness, this time on a country level. The pressure exerted by stakeholders is then determined as:

$$Country\_pressure = \frac{Country\_EPI}{Country\_EPI\_max} \tag{5.11}$$

$$Relative\_size = \frac{Production\_size}{Company\_size\_max} \tag{5.12}$$

$$Stakeholder\_pressure = Country\_pressure \times (1 - (Relative\_size \times Size\_mp)) \tag{5.13}$$

Next, the agent determines to what extent its competitors are already taking climate action (i.e. setting SBTs). In doing so, the steel company defines how many of its competitors have committed to setting targets. The firm then compares this number to its total competitor base and estimates the peer pressure originating from its competitors' actions:

$$Competitor\_commitment = \frac{Committed\_competitors}{Total\_competitors} \tag{5.14}$$

The pressure from other, not necessarily competing, steelmakers is determined in a similar way. Concretely, companies value what their allies do more when they are less individualistic and more collectivist in nature. In other words, the lower a company's score on the Hofstede dimension of individualism, the more they value the actions of their allies:

$$Alliance\_commitment = \frac{Hof\_upper\_bound - Hof\_ind}{100} \times \frac{Committed\_allies}{Number\_allies} \tag{5.15}$$

Lastly, as for 'attitude', a weighted sum of all variables is computed (again, see Appendix B for an elaboration on the weights used). The outcome of this is the total score for 'subjective norm' of a particular company at a specific moment in time:

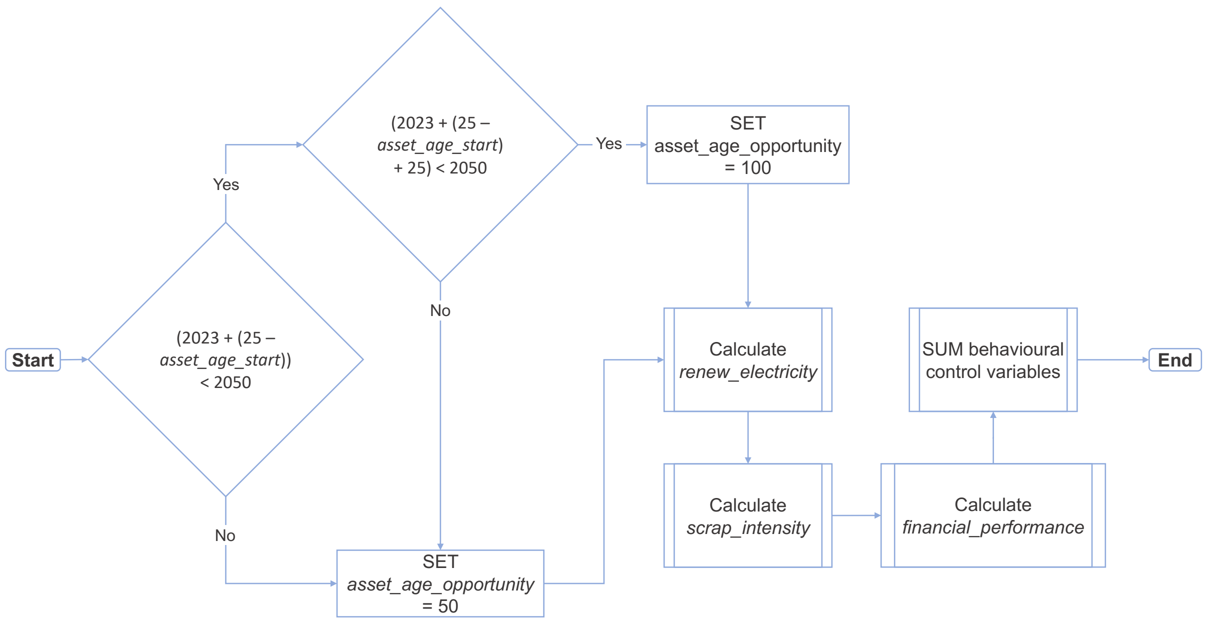
$$Subjective\_norm = \sum(Variable\_w \times Variable) \tag{5.16}$$

Now where *Variable* represents the different independent variables and parameters directly influencing a company's subjective norm. *Variable_w* again represents the weight given to each specific variable.

Determining 'behavioural control'

If the intention to pursue SBT adoption exists, the Theory of Planned Behaviour posits that an agent must feel it has some control over achieving potential science-based targets. If the agent does not believe it can accomplish the emission reductions necessary following the latest climate science, it will not engage in committing to SBTs. This perception of control is determined following Figure 5.6.

Figure 5.6: Overview of agents' process to determine their control over achieving potential



At first, companies assess the (average) age of their steel-making capacity. Based on this value, they set a score that reflects the opportunities of the company to decarbonise in the near future. With a period of 25 years between major replacement or refurbishment opportunities (Section 3.3), it is calculated how many of these moments will occur between the model start and 2050 (i.e. the date by which most policies and the SBTi aim for net zero). As the model starts in 2023, it is mathematically impossible that more than two major maintenance windows occur before 2050. Hence, if there are two opportunities for replacement before 2050, the maximum score (100) is assigned to the relevant variable for this company. Otherwise, a score of 50 is given, representing one opportunity by 2050[5].

After this process, steel companies determine to what extent they have access to low-carbon electricity and can produce using secondary steel scrap (see Appendix A.5 for an elaboration on the growth rate and initial values):

$$Renew\_electricity = (Renew\_elec\_growth \times t) + Renew\_elec\_start \tag{5.17}$$

$$Scrap\_intensity = (Si\_growth \times t) + Si\_start \tag{5.18}$$

[5]Note: since there are 28 years between the start of the model and 2050, virtually all companies will have at least one opportunity for a big overhaul of their steel-making facilities. As such, companies can only be assigned a value of 100 or 50 for the variable that reflects the decarbonisation opportunity with respect to asset age.

Moreover, every company performing the decision-making process assesses its financial performance, which is a crucial determinant for companies to invest in low-carbon technologies (Section 3.3). Due to time constraints and challenges in gathering adequate financial information, companies are assigned a random value for *Financial_performance* at the model start. However, each firm's financial performance varies randomly over time as is explained in Appendix A.5.

Altogether, these variables constitute the (perceived) behavioural control of the agent, which moderates the relation between intent and action (Bosnjak et al., 2020):

$$Behavioural\_control = \sum(Variable\_w \times Variable) \tag{5.19}$$

Variable here represents the different independent variables and parameters directly influencing a company's subjective norm. *Variable_w* again represents the weight given to each specific variable.

5.2 Evaluating the model

In ABM based studies, there are two important steps to be undertaken in order to ensure model validity. While coding the computational model, it is imperative to continuously assess if the conceptualisation of the model is accurately being translated into the programmed simulation model (Van Dam et al., 2012). In addition to this process of verification, it should be made clear what the actual use of a model is and to what degree is can adequately explain system behaviours. This process is called validation and it outlines to what extent the agent-based model can convincingly answer the research questions. Both verification and validation require swift changes to the model if inconsistencies are found. As such, they are iterative processes that were conducted in parallel to the development of the ABM.

Verification

The process of verifying the agent-based model was based on the book '*Agent-Based Modelling of Socio-Technical Systems'* by Van Dam et al. (2012). The authors of the book propose three phases of verification that result in a model that is consistent with its conceptualisation.

Testing individual agents

Firstly, Van Dam et al. (2012) suggest the testing of individual agents to verify their behaviour under certain predicted and extreme circumstances. The steel companies in the model were as such subjected to a number of tests used to verify if their behaviour matched expectations. For example, since the agents in the model only act if the scores for certain constructs reach above a threshold, individual agents were manually followed to study if their behaviour actually changed when surpassing the set boundary. Apart from this higher-level testing, the modelled computations that determine agents' scores for the most important model variables (see Figure 5.1) were also tracked for accuracy. Additionally, single agents were given extreme values (e.g. values below zero) for different parameters, to test if the model did not run into mathematical problems (e.g. division by zero) and behaviour remained as expected[6]. Since much of the input data of the model is linked to geographical location, such tests were conducted on companies from all countries.

Testing a minimal model

Apart from testing if single agents behave as expected, it is important to verify the interaction of agents in the model. Agent interactions are one of the distinguishing factors of agent-based models, hence it is important to evaluate if the modelled interaction is in line with what was conceptualised. Considering the iterative nature of this process, the verification of model interactions is first done in a minimal model. In order to conduct this verification step, similar checks are used as with the single agent verification. Apart from this, there is now more focus on the variables that are directly or indirectly influenced by the behaviour of other agents. Again there is a special focus on verifying that the model works as conceptualised for different types of agents. One concrete example of such testing concerns for instance the verification that companies only respond to the behaviour of allies (i.e. the companies are linked) and competitors (i.e. the companies exist on the same continent and are similar in size).

Testing the full model

Once the behaviour of the minimal model is in line with the conceptualisation, it is essential to verify the simulated behaviour of the full system. Similar to before, checks such as 'breaking the agent' (i.e. testing behaviour under circumstances of extreme values) and 'theoretical prediction' (e.g. verifying that interactions are in line with expectations) are used, though now for the complete model with all steelmakers. Additionally, the weighting of variables in order to compute 'attitude', 'subjective norm' and 'behavioural control' is tested in this step. More specifically, full weight is manually given to one variable at a time (per construct) and the resulting system behaviour is compared to the system's behaviour under normal weighting. Throughout all these verification checks, logical reasoning is used to ensure that not only the eventual model outcome but also the behaviour of the model throughout a simulation run is representative of the conceptual model.

[6]Expected behaviour can also entail that the agent does not undertake action.

Additional verification

On top of the verification steps proposed by Van Dam et al. (2012), two more verification methods are used in this study. In line with Balci (1994), bottom-up testing is conducted to at first evaluate if all three sub-models - those that lead to the determination of a score for 'attitude', 'subjective norm' and 'behavioural control' - work as intended, before the complete model's behaviour is subjected to verification tests. Additionally, the work of Wilensky et al. (2015) is followed by including user-messages that halt a simulation when appropriate. In doing so, it is ensured that future alterations do not unconsciously disrupt the previously intended workings of the model.

Validation

In addition to assessing a model's alignment with what the model was set out to represent, the validation of the ABM should be discussed. Van Dam et al. (2012) argue that validation can be conducted through a number of methods. Before delving into these techniques and how they were applied, it is important to elaborate on the purpose of this ABM (see Appendix A.1 for more detail). More precisely, it is crucial to mention that counting the number of companies that commit in any specific scenario is not the aim of this study. Rather, tracking and quantifying for example the commitment of companies is a metric that can be used for comparison across scenarios. No value should thus be given to the absolute outputs of the ABM. Only by comparing the relative changes between scenarios can findings be concluded, thus making it important to mention that the model validation focused on this premise.

Since the system under study occurs in the real world and there is historical data available, Van Dam et al. (2012) argue that historical replay can be an appropriate validation method. The ABM of this study is, however, from the outset calibrated in a way that does not necessarily fit precisely with the historical data regarding SBT commitment in the steel industry. As will be elaborated upon, this is useful for the purpose of the study as it allows for clear comparisons across scenarios. As a result, though, historical validation is not the most useful method to assess the model's validity. Instead, two of the other proposed validation methods by Van Dam et al. (2012) were used. A first approach to ensure the credibility of the ABM is through expert validation. In order to ensure that the conceptualisation was valid from a modeller's perspective, the conceptual model (e.g. the incorporation of the Theory of Planned Behaviour) was validated by a number of ABM experts. On top of this, the model outcomes in the form of identified patterns and system behaviour were validated with steel industry experts. As a second useful validation method for this study, the model outcomes can be compared to existing literature on the topic. However, since this study was conducted under time constraints, there are of course limitations to how representative the model is of the real world system under study. On the other hand, the aim of the model is not to define a specific number of companies that can be expected to commit under a certain scenario, but rather to give a more clear idea of what drives company behaviour towards commitment. As such, the outcomes of this study can still be useful when interpreted correctly and a multitude of patterns that occur in the real world (and are recorded in literature) are also observable in the model. These patterns will not be mentioned here, but they are discussed in detail in Chapter 8.

5.3 Experimental setup

In this section the experiments are explained. The focus here is specifically on describing the various analyses and scenarios that were conducted, while the next chapter deals with the outcomes.

Sensitivity analysis

In order to define the input values of the baseline model and test for its robustness, a local one-factor-at-a-time (OFAT) sensitivity analysis is performed. In essence, this method entails that the nominal parameter values corresponding to the baseline model are varied one by one, while keeping all other factors constant. In doing so, the researcher can make inferences regarding the relation between the changed parameter and model output (Ten Broeke et al., 2016). As Ten Broeke et al. (2016) suggest, the altered parameters are often changed over a certain range in OFAT sensitivity analyses. In order to align this analysis with the time and computing power constraints of this study, not all parameters of the model were incorporated and the space between steps within the range for variation of the analysed parameters was limited. The parameters that were included in the analysis were chosen based on the uncertainty inherent in the nominal value of the base scenario. Table 5.3 outlines the sensitivity scenarios that were tested. As the most important output metric, the total number of steel company commitments was tracked over time to compare the base scenario with the sensitivity scenarios.

Looking at Table 5.3, the outlined parameters and variables can be grouped into two categories. First of all, there are those parameters that are included in the model because a review of the literature on company climate action deemed them important[7]. The second group consists of the model specific factors *Standard_threshold* and *Threshold_mp* - which are both used in the model to define each company's *Long_term_threshold* - and *Create_links*. For both the base model and the OFAT sensitivity analysis, the number of repetitions used is 50. This number is believed sufficient to reduce the influence of randomness on the model results, while limiting the needed computing power.

[7]This includes for example *Large_size_threshold*, as this parameter is used to determine if a company is qualified as large. In Section 3.3 it was determined that the size of a company is an important aspect when considering its behaviour regarding climate action.

Table 5.3: Overview of the parameters (from literature and model specific) and parameter variations used in the sensitivity analysis

Parameter	Nominal value	Variation*	Unit
Price_threshold	95	[80; 5; 110]	€
Large_size_threshold	10	[6.5 & 13.5]	Mt
Medium_size_threshold	4.5	[2.925 & 6.075]	Mt
Size_effect_diversity	0.3	[0.0; 0.15; 0.6]	NA
Size_effect_board	0.3	[0.0; 0.15; 0.6]	NA
Financial_performance_change	4	[0; 1; 8]	NA
Standard_threshold	38**	[30; 1; 45]	NA
Create_links	2	[0; 1; 4]	NA
Threshold_mp	0.5	[0.0 & 1.0]	NA

**A denotation of [X; Y; Z] entails that the parameter was varied in the range from X (included) to Z (included) with steps of Y. A denotation of [X & Y] means that the parameter was varied to exactly these values.*

***The value of 38 was set after running the sensitivity analysis to determine at what value for standard_threshold approximately 50% of companies would be committed by the end of 2035 (see Section 6.3).*

Factors from literature

Though the parameters and variables specified in the blue columns in Table 5.3 are based on literature, interpretation remains subjective. Concerning *Size_effect_diversity* and *Size_effect_board*, the studied literature suggests that there is a positive relation between a firm's size and its board diversity and number of board members. However, the existing studies do not report any useful effect sizes that could be used to quantify the effect of firm size on board size and diversity. As such, the size of this effect that was included in the baseline model may not be completely in line with what the authors of the existing studies found. This makes it relevant to include these factors in the sensitivity analysis, though it simultaneously results in a difficulty to determine by how much to vary the respective parameters. Consequently, it was chosen that both variables are varied within a range of 100% of the nominal value. This furthermore allowed to run a scenario excluding each effect.

Related to the above, two parameters are included that determine the size classification of the modelled companies. Specifically, *Large_size_threshold* defines above which production output companies are considered large, while *Medium_size_threshold* delineates the same but then for a classification of 'medium'. The nominal values for both were established by varying each and locking them in on values that resulted in approximately one-fourth of companies classified as 'large', one-fourth qualified as 'medium' and half as 'small'[8]. To see if the results are decently robust with respect to company size

[8]Though the focus of this study is not necessarily on small or medium-sized companies, this classification is solely used for modelling purposes. The population of modelled companies still represents the operations of the largest steelmakers.

classification, the sensitivity analysis included a value of +/- 35% for each.

Considering the included *Price_threshold*, the study by Hoffmann et al. (2020) suggested that a carbon price of €55-€95 can already make green H_2 less expensive than grey H_2. As was noted before, this number was based on an analysis of the German market. Consequently, the nominal value used for *Price_threshold* was aligned with the higher value of the range given by Hoffmann et al. (2020). Taking into account that Germany is a developed economy and not all included countries are, it is logical to set a higher value than €95 as the upper-bound of the parameter variation range. Similarly, since Germany's electricity sector is still more fossil-based (see Figure 3.4) than the electricity mix of certain other included countries, it is also sensible to set the lower-bound of the parameter variation below €95. Since the sensitivity analysis is focused on assessing the robustness of the baseline model, it was deemed sufficient to include a range of €80-€110 with steps of €5.

Regarding *Financial_performance_change*, the financial performance of a company in the future is inherently uncertain. This is why *Financial_performance_change* was included in the model and it simultaneously explains the need to test the model's sensitivity with respect to this parameter. In order to test how the model performs when the companies' financial performance does not change over time, the lower limit of the parameter variation range is set to zero. The upper boundary is consequently set with an increase of 100% of the nominal value.

Factors specific to the model

Three parameters are included in the sensitivity analysis that are particular to the ABM of this study. First of all, *Create_links* determines how many linkages each company is asked to create with other steelmakers when the model is set up. Since the network of the model is determined randomly and the initial number of links is not based on literature, it is important to assess the sensitivity of the model output with respect to this factor. In order to see what the effect would be of a 'network' in which no companies were linked, the minimum number of links each company was asked to create was set to zero. On the other hand, since Den Hartigh et al. (2005) show that the network of a company-focused ABM can be influential, the sensitivity with regards to more links developed per company was also tested.

Secondly, two parameters that influence a company's *Long_term_threshold* are included in the sensitivity analysis. Whereas the *Standard_threshold* sets a minimum value for *Long_term_threshold* that is adopted by all companies, *Threshold_mp* incorporates how much importance is given to a company's

Hofstede long term orientation score when determining *Long_term_threshold*. The value for *Threshold_mp* is standard set to 0.5, so that *Long_term_threshold* is artificially kept relatively low. This is done in line with the purpose of the study, which is to compare across scenarios. If no or only very few companies commit in the baseline scenario, it is more challenging to make conclusions about scenarios where even less companies commit. On a similar note, since *Standard_threshold* is arguably the most significant parameter in the model, a wide range of values was tested for this specific factor. In order to be able to clearly compare the different scenarios that will be simulated using the ABM, the *Standard_threshold* is set to a value that corresponds with approximately 50% of companies being committed by the end of 2035.

Exploratory experiments

Complementary to the OFAT sensitivity analysis, a number of so-called exploratory experiments are conducted. These experiments model 'what if' scenarios, based on uncertainties that are not tested in the sensitivity analysis but do deserve some attention. Moreover, running these experiments allows to build a better understanding of the workings of the model and what could potentially be important to stimulate companies towards climate action. Altogether, four exploratory scenario groups are modelled and each specific scenario will be conducted using 50 repetitions:

- **Exploratory ownership scenarios** - Since the ownership status of companies is assigned using data from a couple decades ago, it is relevant and interesting to delve deeper into the effect of ownership. As such, the ownership status of the steelmakers will be varied, so that in each of three scenarios all companies have the same form of ownership (state-owned, publicly listed or private).

- **Exploratory scrap intensity scenarios** - Due to the uncertainty inherent in the projection of scrap availability and future steel production, it is worthwhile to consider what changes to the modelled *Scrap_intensity* do to the overall commitments of companies. *Scrap_intensity* is therefore changed in two scenarios: i) the variable is kept constant at the level of early 2023 and ii) the baseline slope (*Si_slope*) is doubled.

- **Exploratory size classification scenarios** - As company size is a factor that influences a number of different parameters, an exploratory experiment is conducted on top of the performed sensitivity analysis regarding size. In a first experiment, all companies are classified as 'large' and in a second and third they are all assigned the label 'medium' and 'small', respectively.

Table 5.4: Weights for the baseline model and different exploratory scenarios (coloring used to indicate the different TPB constructs: attitude, subjective norm and behavioural control)

Variable	**Scenario**				
	Baseline	**Equal**	**Financial**	**Stakeholders**	**Steelmakers**
Board_diversity	0.25	0.2	0.125	0.125	0.25
Board_size_pressure	0.15	0.2	0.125	0.125	0.15
Board_age_pressure	0.125	0.2	0.125	0.125	0.125
Ownership_pressure	0.2	0.2	0.125	0.5	0.2
Price_pressure	0.275	0.2	0.5	0.125	0.275
Stakeholder_pressure	0.4	0.33	0.4	0.5	0.1
Competitor_commitment	0.4	0.33	0.4	0.25	0.5
Alliance_commitment	0.2	0.33	0.2	0.25	0.4
Asset_age_opportunity	0.2	0.25	0.167	0.2	0.2
Renew_electricity	0.25	0.25	0.167	0.25	0.25
Scrap_intensity	0.25	0.25	0.167	0.25	0.25
Financial_performance	0.3	0.25	0.5	0.3	0.3

- **Exploratory weights scenarios** - Since subjectivity was an inherent factor in the determination of the baseline weights, it is important to also assess the model output of simulations in which the weights are varied. More specifically, four different exploratory experiments with respect to weights were conducted (Table 5.4). A first experiment uses equal weights for all variables that relate to a specific construct. For example, all variables related to ’attitude’ are given the same weight. The second scenario simulates that companies put more emphasis on financial factors compared to the other variables[9], whereas the third includes weights that emphasize the importance of a company’s stakeholders.[10] Lastly, the fourth experiment considers a simulation in which the most significance for companies in their SBT commitment decision goes to other steelmakers (i.e. competitors and allies).[11]

[9]Experiments in which the weights for the financial or stakeholder variables are increased result in changes for the weights of the other variables. The following logic is applied in these instances: if the weight of one or more variables is increased in a certain scenario, the ’leftover’ weight is equally divided over the other variables that make up the same construct. The weights used for the variables of the constructs that are not affected remain the same as in the baseline model.

[10]Including owners but excluding other steel companies.

[11]Note that the variable weights used in the model all correspond to a specific variable or parameter, which is in turn linked to one of the three TPB constructs. As such, a scenario putting emphasis on other steel companies will result in higher weights for *Competitor_commitment* and *Alliance_commitment*. Since these two variables together with *Stakeholder_pressure* make up the construct ’subjective norm’ and the weights for each construct must sum to one, increases in the weights for *Competitor_commitment* and *Alliance_commitment* will automatically result in a decrease of the weight for *Stakeholder_pressure*.

Scenario testing

As a final approach to be able to understand the model and its behaviour to a detailed level, a number of more comprehensive scenarios are simulated and studied. In contrast to the sensitivity and exploratory experiments, the scenario testing mentioned here focuses on the emergent system behaviour when multiple independent variables or parameters are altered simultaneously. Again, all specific scenarios will be run for a total of 50 repetitions to account for the variability that is caused by randomness in the model.

- **Carbon pricing scenarios** - Carbon pricing is believed to be one of the most important levers that governments can use to stimulate climate change mitigation efforts. However, there is much discussion on what price levels are adequate to ensure a net zero future. Moreover, combating climate change is a global challenge, hence setting a carbon price on a regional level may result in carbon leakage and thus underwhelming effects. Since the carbon prices that are currently in place are likely not yet high enough and many regions have not yet adopted a carbon pricing scheme, these scenarios focus on this phenomenon. Specifically, three carbon pricing scenarios are modelled based on the numbers used by IEA (2022b) in their policies, pledges and net zero scenarios. The incorporated price levels are shown in Table 5.5. In addition, the distribution of free allowances to the steel sector is varied. That is, for each IEA pricing scenario, the model is run with free allowances and without[12]. For comparison, the base model is also simulated without the availability of free emission allowances for the steel companies.

- **Stakeholder scenarios** - Industries of which it is well known that they are responsible for a large share of man-made GHG emissions have a higher level of visibility towards stakeholders. Steel is one such industry, which explains why *Stakeholder_pressure* has received an important role in the determination of a company's perceived social pressure in the ABM. However, the pressure exerted by stakeholders on the steelmakers is believed an important lever for external (e.g. NGOs) and internal (e.g. owners) parties. By utilising this lever, it is hypothesised that stakeholders other than the corporate board can stimulate more ambitious climate action. One such stakeholder is the SBTi, which currently already runs a campaign with CDP to effectively put pressure on so-called high-impact companies (CDP, 2022a). They do this by leveraging their networks, increasing the pressure exerted by supply chain stakeholders and financial institutions. The rationale for the modelled stakeholder scenarios is similar to the campaign with CDP. Instead

[12]By default, no free allowances are modelled for all countries where there is not currently already a carbon price in the ABM. The uncertainty of time-frames and quantities in potential free-allowance schemes makes it challenging to accurately estimate how many allowances the steel companies in these countries would receive in the future, hence this analysis is excluded.

of focusing on all high-impact companies, though, the scenarios include a specific focus of the SBTi on the supply chain actors and financial institutions linked to the steel sector. However, since the complex business networks of suppliers, customers and financiers are not modelled, no distinctions - except for those based on a company's ownership, see below - are made between companies in the effect of increased stakeholder pressures[13].

Consequently, the stakeholder scenarios incorporate increased pressure from two groups: i) general stakeholders (through *Stakeholder_pressure*) and financiers/financial institutions (through *Ownership_pressure*). Regarding the latter, it is assumed that financial institutions either hold part of a company's ownership or are able to put stringent pressure on a steelmaker's owners. This is believed especially the case for publicly listed and private companies, hence it is these firms that are modelled to have increased *Ownership_pressure* in the stakeholder scenarios. In the scenarios, both *Stakeholder_pressure* and *Ownership_pressure* are simulated to increase by 0% (i.e. the baseline value), 10%, 20% or 30%. Since two variables are altered and they can both take one of four values, a total of 16 stakeholder scenarios are simulated.

- **Network scenarios** - In this last group of scenarios, modifications to the network and interactions of steelmakers are incorporated. The logic behind the network scenarios follows from the use of Expert Advisory Groups by the SBTi, which the initiative organises to determine adequate decarbonisation pathways for hard-to-abate sectors (B. Chan, 2022). Instead of focusing on decarbonisation pathways, however, it is hypothesised that the SBTi organises such working groups to build a shared vision of a decarbonised steel industry. By portraying that a low-carbon steel industry is possible through cooperation, it is the aim that the trust among steelmakers increases and the companies start working together more. Three parameters are changed in the simulations to incorporate these effects into the model. First of all, the number of links that each steel company creates (*Create_links*) is set to two (baseline), four, six and eight. Following the expected increase in trust among the modelled companies, the steelmakers will value more strongly what their allies are doing. Hence, the value for *Alliance_commitment* is artificially increased by 0% (baseline), 10% or 20% in the scenarios. Another assumed effect of the increase in trust is the decrease of the threshold used to define when a company perceives the social pressure as too

[13]That is, the campaign with the CDP utilises both the SBTi's and CDP's network of companies that have set SBTs, are members of the CDP Supply Chain group or are part of the Capital Market Signatories. Additionally, the SBTi puts extra focus on targeting those companies that are part of the value chain of committed companies that have set supplier-engagement targets. However, it is not incorporated in the model which companies are part of these networks or groups, who the financiers of companies are and who their supply chain actors are. As such, no distinction is made between companies (exception state-owned companies, see text) when the extra stakeholder pressures are modelled

much. Consequently, the *Long_term_threshold* for *Subjective_norm* is decreased by 0% (baseline), 10%, 20% and 30%. Altogether, three parameters are adapted in the network scenarios, resulting in a total of 48 scenarios.

Table 5.5: Carbon prices used (Source: IEA (2022b))

	2023	**2035**		
	Base	**Policies**	**Pledges**	**Net Zero**
EU	83,30	93,68	148,03	169,21
Russia	0	0,00	11,86	60,00
Turkey	0	0,00	123,53	144,71
Ukraine	0	0,00	11,86	60,00
China	7,32	32,15	79,80	115,09
India	0	0,00	77,65	112,94
South Korea	12,51	50,97	127,21	148,39
Japan	0	0,00	123,53	144,71
United States	0	0,00	123,53	144,71
Canada	43,13	56,59	136,21	157,39
Mexico	0	0,00	11,86	60,00

Note: The values for 2035 were computed by linearly extrapolating the 2023 carbon price of each country using that country's estimated carbon price in 2040.

5.4 Conclusion

In conclusion, an agent-based model is developed that incorporates the largest global steel companies. Each company is given a number of characteristics and is influenced by external factors that give rise to its perception of SBT adoption. Agents for example study what their counterparts are doing, are influenced by their cultural backgrounds and are aware of the financial challenges associated with deep decarbonisation. The decision-making process of the modelled companies is given structure by use of the Theory of Planned Behaviour. As such, the steelmakers will only commit when they feel able to decarbonise to the extent possible as required by potential science-based targets. The ABM will then be tested for its sensitivity to factors with substantial uncertainty that lay at its foundation. The findings of this sensitivity analysis will be acknowledged when running exploratory experiments and conducting scenario tests. These in turn are carried out to investigate how the model works and how companies can be stimulated to take climate action most effectively. This is discussed in the next chapter.

Chapter 6

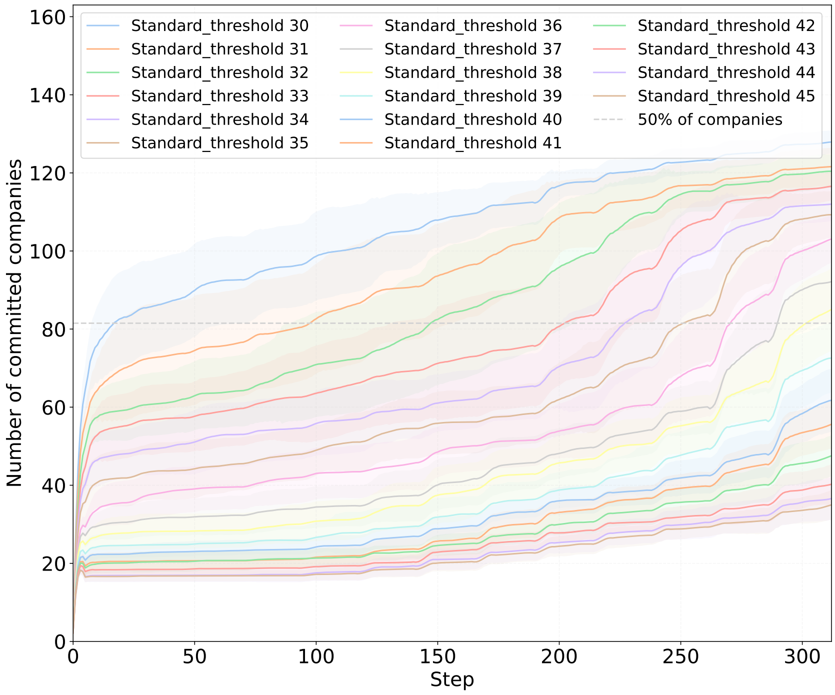
The Base Model

As was elaborated on in Section 5.3, the sensitivity analysis was conducted for two purposes: i) define the nominal value for *Standard_threshold* so that approximately half of all companies is committed by the end of 2035 and ii) test the robustness of the model's output with respect to changes in certain parameters. This chapter first deals with the setting up of the base model, by defining an adequate value for *Standard_threshold*. The resulting baseline is then discussed into detail in Section 6.2. Lastly, the second objective of the conducted sensitivity analysis is presented. Section 6.3 elaborates on the robustness of the base model and outlines which factors are important to consider when interpreting the model results.

6.1 Defining the base model

In order to find the value for *Standard_threshold* that results in approximately half of all companies committing, the model was first calibrated with the other nominal values as outlined in Table 5.3. Consequently, the model was run while only varying *Standard_threshold* over the range specified in Table 5.3. Figure 6.1 depicts the average number of companies that committed in these scenarios over the time horizon of the model. As the figure shows, on average almost 50% of companies is committed at the end of the simulation at a *Standard_threshold* of 38. This value was therefore defined as the nominal value that corresponds to the base model used in further analyses.

Figure 6.1: Effect of altering the long term threshold of companies - by varying the value for *Standard_threshold* between 30 and 45



Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

6.2 Outcome of the base model

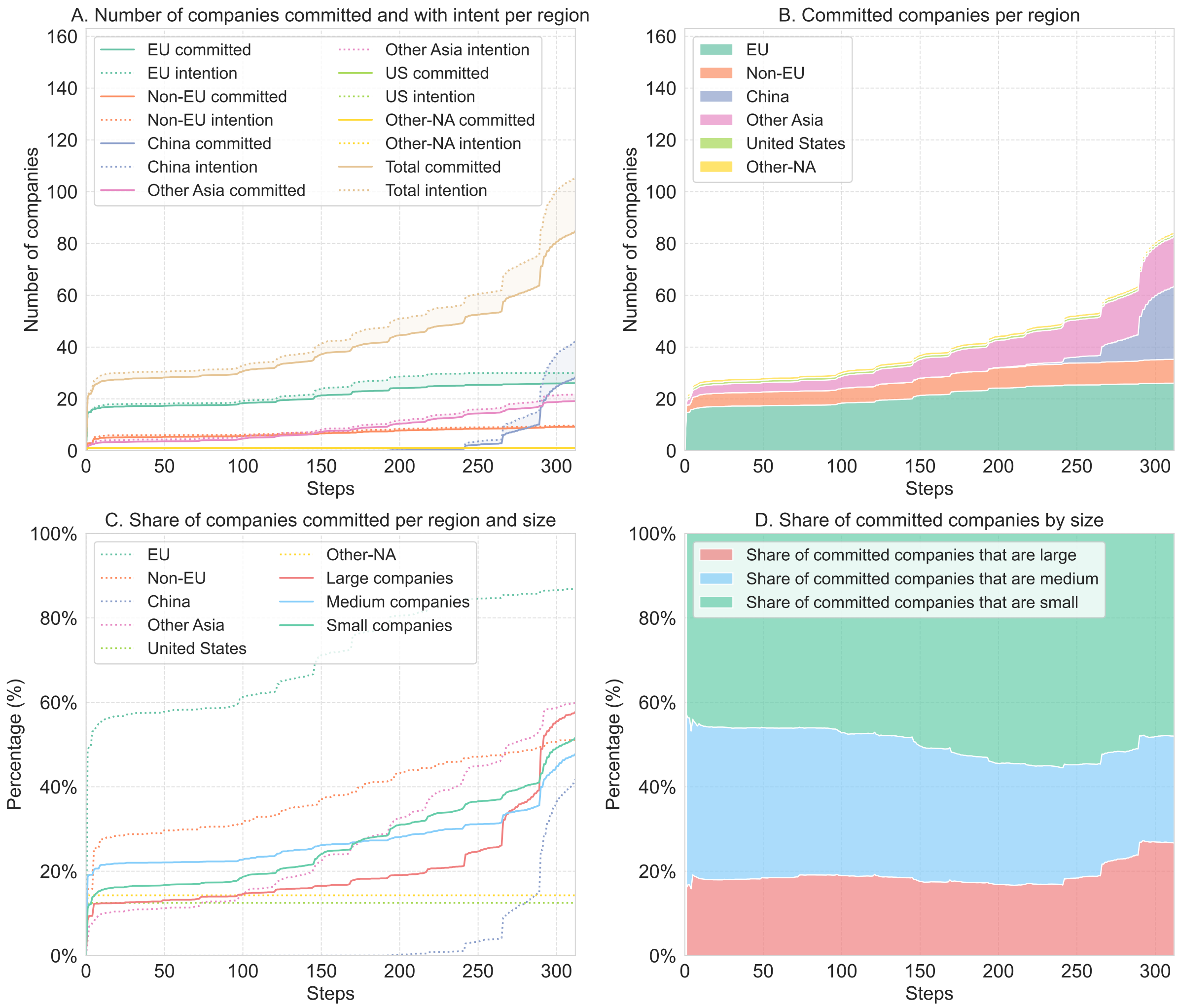
Regarding the baseline model, more factors than just the number of total commitments were tracked. The main output is plotted in Figure 6.2, whereas Figure 6.3 can be used to make sense of companies' commitment behaviour

As Figure 6.2B&C show, though the total number of commitments increased substantially from the model start onwards, large commitment differences occur between regions. At the simulation start, the number of commitments rises most rapidly in the EU. However, over the course of the experiment, especially the number of committing companies in Asia rises. Noteworthy is also that the number of commitments in Other-NA is stable over time, even though the Canadian companies are subject to a rising carbon price. Figure 6.2A further indicates that there is quite a substantial commitment-gap[1] for companies in both the EU and China. A large difference exists in that the EU commitment-gap is already predominant about halfway into the simulation and eventually decreases again, while

[1] A commitment-gap is what occurs when companies develop the intention to commit, but do not actually commit due to insufficient behavioural control.

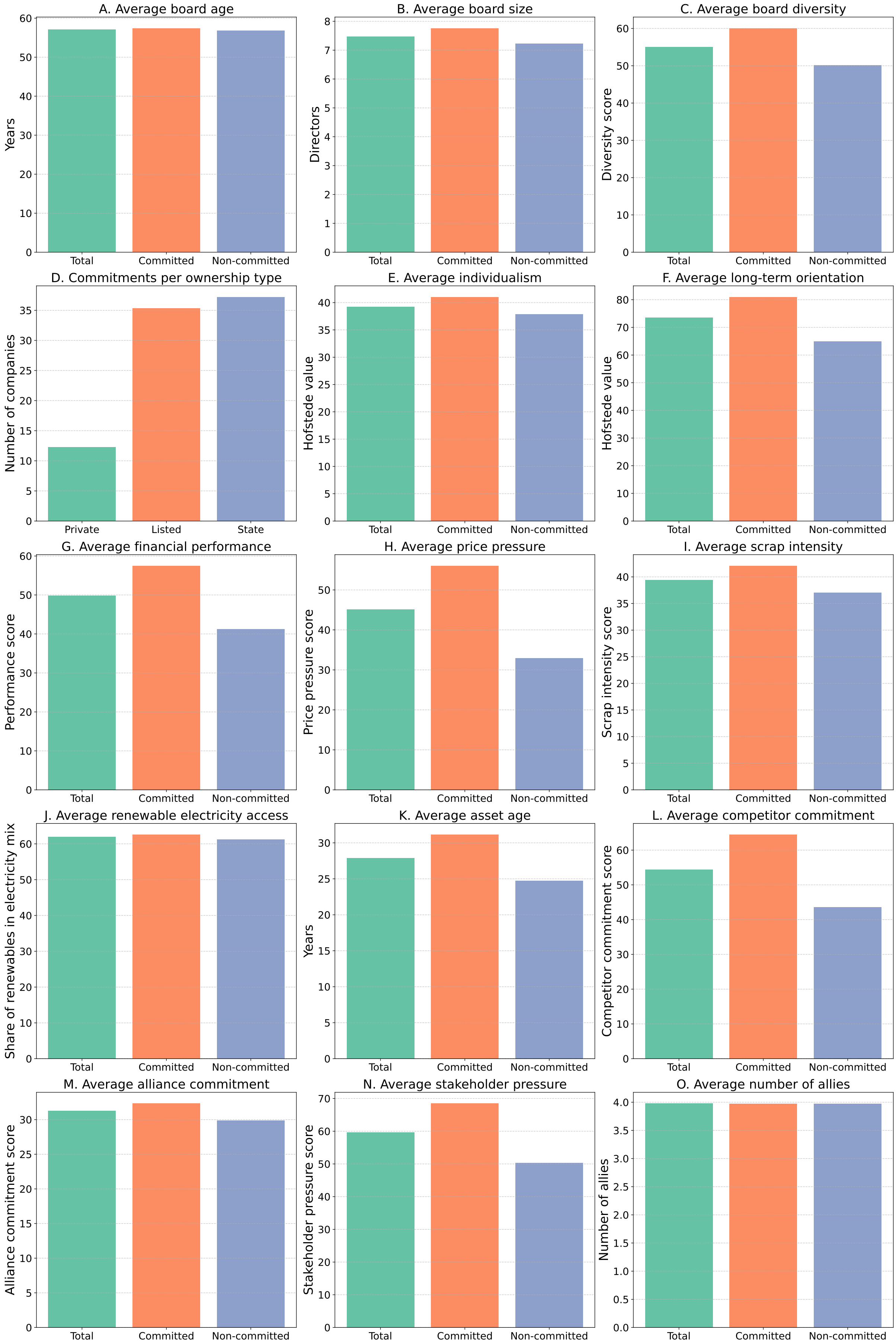
Chinese companies only become motivated to commit at the simulation's ending. As such, Figure 6.2C shows that almost 90% of EU companies is committed at model end, while this figure for China is only about 40%. Of the committed companies, most are small (Figure 6.2D). Figure 6.2C further depicts that in relative terms it is initially mostly medium and small companies committing, while their larger counterparts follow suit later. This last push from the large companies results in them being slightly over-represented among final committers[2].

Figure 6.2: Describing sub-figures for the baseline scenario



[2]This can be inferred from Figure 6.2D by taking into account that about 24% of companies is large.

Figure 6.3: Comparison characteristics for the baseline scenario



When interpreting Figure 6.3, it can be inferred which of the main factors (i.e. those included in Figure 5.1) mainly drive company behaviour in the model. From the factors relating to 'attitude', a clear difference between the committed and non-committed companies can be seen for board diversity (Figure 6.3C) and carbon price (Figure 6.3H). Regarding 'subjective norm', companies' long term orientation (Figure 6.3F) is important, together with their perceived pressure from competitors (Figure 6.3L) and stakeholders (Figure 6.3N). Interestingly, the behaviour of allies does not seem too important for steelmakers. Important drivers of positive behavioural control are mainly financial performance (Figure 6.3G) and the age of production capacity (Figure 6.3K).

That the number of commitments increases over the time-span of the model follows logically from the modelling choices made. Certain drivers of commitment - such as carbon pricing and board diversity - increase as time progresses, resulting in more favourable conditions to commit. On the other hand, the absence of rising commitments in Other-NA signals that carbon pricing is not responsible for commitments on its own. Moreover, many of the important drivers that are identified based on Figure 6.3 result from the weights used. For example, *Competitor_commitment* weighs more heavily towards 'subjective norm' than *Alliance_commitment*, which at least partially explains why the output shows that the former is a substantial driver and the latter is not. Nonetheless, the weights were determined based on an assessment of available literature and reasonable logic (see Appendix B). Consequently, it is still possible to make conclusions based on the model outcomes, though the effect of the chosen weights should be acknowledged. To better understand the influence of the chosen weights, some exploratory experiments were conducted that are discussed in Section 7.1.

That the EU is a front runner regarding commitments follows the simple fact that the model is setup by automatically committing the included steel companies that are in real life also committed (see Appendix E). Most of these are from the EU. These companies in general also have relatively old production capacity, which could explain why Figure 6.3K shows that capacity age is much higher among committed companies. However, the average asset age in China is much lower and at the end of the model many Chinese firms commit. This indicates that old capacity is an important driver of commitment early on, when other behavioural control factors are not yet sufficiently available. The companies with newer production assets are more likely to commit when commitment has become more normal and other factors that enable decarbonisation are more prevalent. This phenomenon signals that it could be worthwhile for the SBTi to first engage with those companies that need to replace a large share of their steel-making technologies in the near future. The initiative then indirectly builds up the pressure on other companies, which are often non-European.

Concerning the eventual rise of Asian commitments, it is likely that this is largely driven by external factors. Since the Asian countries, apart from India, are all very much long term oriented, their threshold for intention or commitment (i.e. *Long_term_threshold*) is in general relatively low. The number of commitments among the companies on this continent mainly rises at the end of the simulation, and many company-internal characteristics are already defined at the model's beginning. Therefore taking into account the importance of factors like carbon pricing and competitor behaviour (Figure 6.3) it is perceivable that contextual factors like these are the main reason that Asian companies commit. Though, it should be noted that companies' features probably still play a substantial, more indirect, role, as Figure 6.3 also shows that for example board diversity and financial performance are important assets of committing companies. Since both these variables have the possibility to increase over time, higher scores for company-specific characteristics later on in the model can also partially explain the late rise of Asian commitments.

Then, regarding the commitment-gap that is prevalent especially in the EU and China. In the EU, it is interesting that the gap first increases, and then gradually declines again. The carbon price in this region reaches the €95 *Price_threshold* in 2026 (i.e. just before step 100) and *Price_pressure* on EU firms keeps increasing until approximately step 240. Since carbon pricing plays on a firm's attitude and Figure 6.3 shows that committed companies are on average subjected to a higher carbon price, it is likely that this variable results in the increasing number of positive intentions. However, when *Price_pressure* maxes out, the commitment-gap decreases again as the number of commitments is able to gradually catch up with the developed intentions through rising renewables access and scrap intensity. For China, the carbon price only reaches the set *Price_threshold* in 2034 (Figure C.5), and the *Price_pressure* starts rising more rapidly at the model's end as well. Therefore, it is probable that the commitment-gap found for both EU and Chinese companies is the result of modelled carbon price pressures. To a certain extent this could be expected, as *Price_pressure* is modelled as very important for companies (Table 5.4). However, a company's intention and commitment decision are not only driven by a company's attitude - which incorporates carbon pricing. Thus, it is still interesting to see the correlation between an increase in *Price_pressure*, positive intentions and increased commitments.

Lastly, it is interesting that there are relatively more large companies committed at the simulation's end than either medium or small companies. Though sizes vary strongly among firms - and some of the largest companies were split to account for the international operations of the companies (Appendix A.2) - it is very probable that most large firms operate in Asia or China specifically. Hence, the increasing diffusion of targets in China, which has been explained previously, is the likely cause of the late rise of large companies' commitments.

Concretely, it seems like the early rise of commitments in the EU follows the representation of the real world in the model. However, it is also found that the companies in this region react quickly to a rising carbon price. The effect of this variable is likely simultaneously the cause for an increasing gap between the number of firms with positive intentions and the number of companies that are committed. Judging the findings of the base model, it seems that focusing on a higher carbon price as soon as possible is therefore one, but only one, part of the solution that results in more climate action among companies. To truly stimulate commitments, effort should also go to establishing the right conditions for companies to achieve potential SBTs (i.e. increasing behavioural control). From the base scenario findings, it results that not even half of all Chinese companies - which are the most represented companies in the model out of all countries - are committed before 2036. Interpreting the wave of commitments and positive intentions that companies in this region develop later on in the simulation, it is believed that moving forward planned interventions like carbon pricing could spur the largest steelmakers towards increased and more urgent climate action.

6.3 Sensitivity results

As was explained in Section 5.3, an OFAT sensitivity analysis was conducted for the most relevant parameters. In order to test the robustness of the model, the total number of commitments is compared between the base model and the sensitivity scenarios. In Appendix C, Figure C.1 to Figure C.8 visualise the results of the sensitivity analysis.

Create_links - What becomes clear from interpreting Figure C.1 is that the modelled linkages between steelmakers result in additional commitments. All simulations with links between companies result in more commitments than the run where the number of connections is zero. However, the number of links does not directly predict if an experiment will result in more commitments than the base case. More concretely, a value for *Create_links* of one results in more commitments than a value of three or four, while a value of two leads to the most commitments. This is likely caused by the used equation for *Alliance_commitment* (Equation (5.15)), which values the share of committed allies and not the absolute number. Hence, if companies have few links but one or more of the linked companies is committed, the score for *Alliance_commitment* will be high. Contrarily, if a company has many allies, it is more exposed to the behaviour of others but does not act as quickly based on that behaviour. Altogether, the lines in Figure C.1 stay close together for the simulations in which links are modelled. Since the inclusion of hypothesised alliances was based on the real world and in order to include a neighbourhood effect, the results seem robust for the purpose of this model.

Financial_performance_change - Considering that the value for *Financial_performance_change* was set randomly and that Figure 6.3 suggests it is an important driver of firm commitment, it is important to analyse if the model results are robust w.r.t. this parameter. From Figure C.2 it shows that varying the values for *Financial_performance_change* does not significantly change the outcome of the model. The lines depicted never vary too strongly and the final number of commitments only slightly differs across sensitivity tests. Though the nominal value for *Financial_performance_change* is thus selected randomly, it does not seem like the chosen value substantially influences the model output.

Large_size_threshold & Medium_size_threshold - Whereas changing the *Large_size_threshold* (Figure C.3) results in only minor differences in commitment, varying the *Medium_size_threshold* (Figure C.3) has a more considerable effect. The sensitivity results for this parameter suggest that the lower the value for *Medium_size_threshold*, the more commitments will occur. This follows logically from the included relations between firm size (classification) and variables that positively influence commitment intention, such as board size and diversity. The model therefore behaves as expected when varying both *Medium_size_threshold* and *Large_size_threshold*, though it is interesting to note that the model is more sensitive to variations in the first mentioned parameter. The exploratory size classification scenarios will help create a better understanding of the system's behaviour with regard to varying company's size classification (Section 7.1).

Price_threshold - As this is one of the most important parameters in the model, it was tested for a wide range of values. For the first three-quarters of the simulations, the number of commitments stays relatively close to each other (Figure C.5). However, at the end of the model substantial divergence occurs. As was discussed previously, it is in this part of the model that the Chinese companies are exposed to rising carbon prices. Since the *Price_threshold* influences to what extent the carbon price puts pressure on companies, it follows logically that the largest divergence effects are found at the last stages of the simulations. Altogether, the results in Figure C.5 show that the level at which *Price_pressure* is set to the maximum value matters. Though the nominal value for *Price_threshold* is thus based on literature, more research should go towards quantifying this variable for each country specifically.

Size_effect_board & Size_effect_diversity - These parameters were incorporated to model the effect of a company's size on that company's board size and board diversity. The sensitivity results indicate that the model is quite robust to variations in both factors (Figure C.6 & Figure C.7). However, Figure C.6 shows that larger values (i.e. 0.45 and 0.6) for *Size_effect_board* result in fewer commitments. This likely follows from the fact that this parameter also ensures that smaller companies have smaller boards, which in turn are modelled as less favourable towards commitment. Interestingly, no such pattern is found for *Size_effect_diversity*. Considering the sensitivity findings for these parameters, though the included effects are based on literature, the effect size is an estimation. Care should therefore go towards better quantifying the effect of especially *Size_effect_board* on companies' SBT commitment behaviour.

Threshold_mp - This variable is used in the equation that determines a company's *Long_term_threshold*. Since the latter is one of the most important factors in the model, accurately setting the *Threshold_mp* is important. As Figure C.8 visualises, the model is highly sensitive to variations in this parameter. The combination of the nominal value for *Threshold_mp* and the set base value for *Standard_threshold* results in approximately half of all companies committing. As such, the used value for *Threshold_mp* is useful for this study. However, if a different value for *Threshold_mp* had been set initially, the calibrated value for *Standard_threshold* would also have differed strongly from the current value. Hence, though the nominal value for *Threshold_mp* suffices for this study, the results of this work should be interpreted carefully while acknowledging the sensitivity of the model to this parameter.

6.4 Conclusion

The sensitivity analysis established that a value of 38 for *Standard_threshold* results in approximately 50% of companies committing. In line with the model conceptualisation, it was found that companies react strongly to carbon pricing. However, the results from the Other-NA region and increasing commitment-gap in the EU and China also make it clear that carbon pricing is not the only solution. Emphasis needs to go to other technological and financial conditions that make it possible for steelmakers to reduce their emissions appropriately. Moreover, it was found that companies with old assets commit earlier than those with newer assets. Specifically, when limiting factors are not yet sufficient for all companies, it can be effective to create an initial base of committers and thereby indirectly increase the pressure on laggards. These findings were found to be robust for the purpose of this study, though the model is sensitive to some parameters. In order to get a better grasp of what drives companies, the next chapter deals with the exploratory experiments and scenario testing results.

Chapter 7

Results

Whereas the previous chapters dealt with the development and setup of the model, this chapter presents the outcomes of running the experiments. First the outcomes of the exploratory experiments are assessed in Section 7.1. Subsequently, Section 7.2 dives into the scenario testing that was performed.

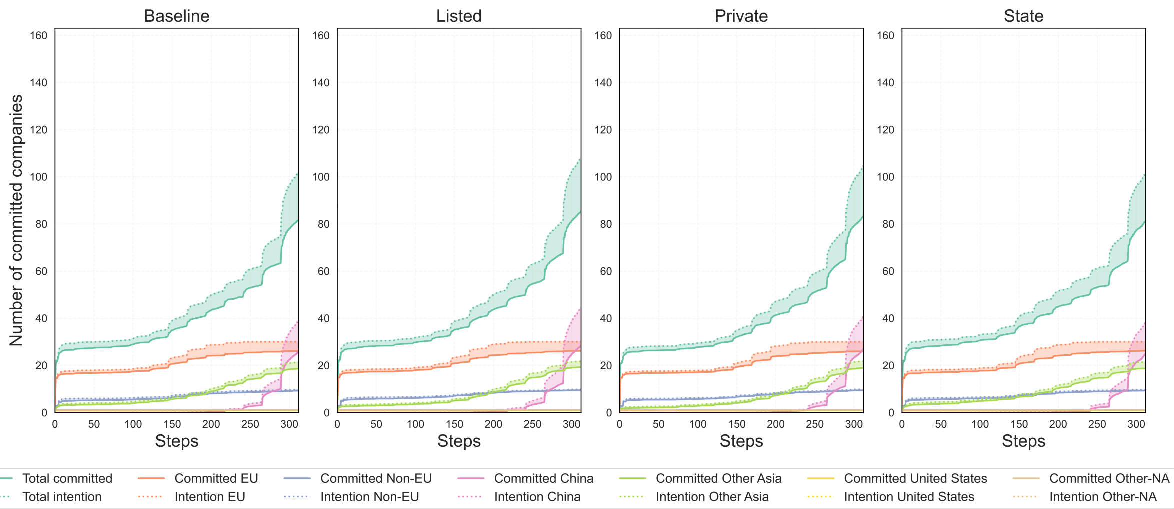
7.1 Exploratory experiment results

In this section, the model outcomes of the exploratory experiments are discussed. The experiments are in more detail described in Section 5.3.

Exploratory ownership scenarios

Figure 7.1 shows the number of commitments per region across the different ownership scenarios. As becomes clear from the figure, there is almost no variation in total commitments between the scenarios. Altogether, only modelling publicly listed companies results in the largest number of total commitments, while a model with all state-owned firms leads to slightly fewer commitments. From this experiment it becomes clear that a company's form ownership is not of substantial importance in the overall decision-making procedure with regards to SBT commitment. Moreover, though the incorporated data from La Porta et al. (1999) is likely outdated, the use of this data does not jeopardise the soundness of the found results.

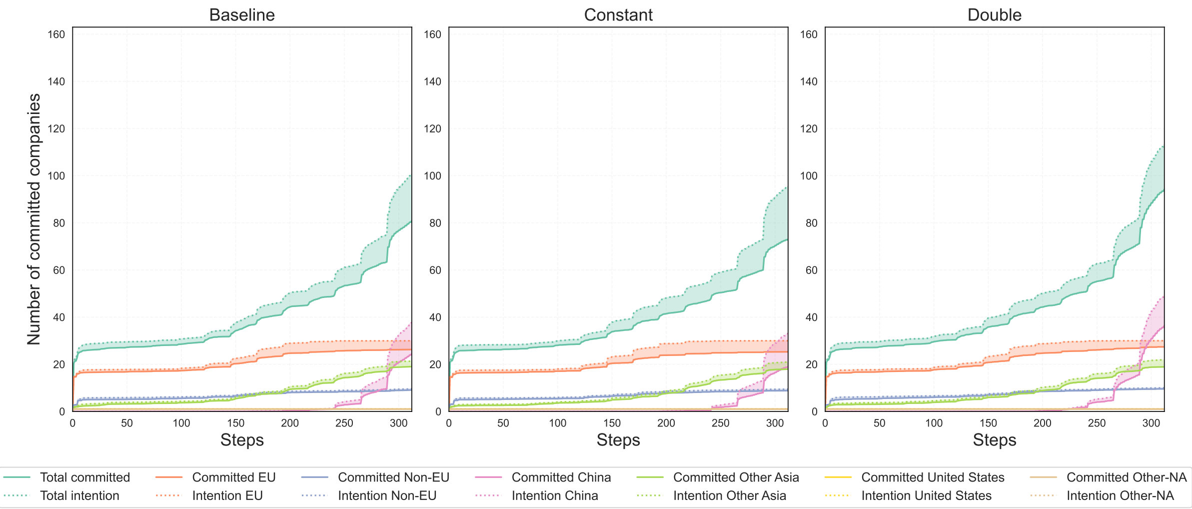
Figure 7.1: Figures depicting the commitments and commitment-gap for the exploratory ownership scenarios



Exploratory scrap intensity scenarios

In contrast to the previously discussed exploratory experiments regarding ownership, the scrap intensity experiments do show varying results. More concretely, when keeping *Scrap_intensity* constant, the number of commitments goes down a little. This is mainly driven by fewer Chinese commitments, as China only marginally ends with more commitments than Other Asia. Additionally, since *Scrap_intensity* is not used in a company's determination of intention, the total commitment-gap does increase slightly. On the contrary, when doubling the slope with which *Scrap_intensity* increases - which also results in a higher value for *Scrap_intensity* at the end of the model, since the baseline value is at one point surpassed - the commitment-gap seems to stay nearly the same (or at least does not decrease as substantially as the total number of commitments increases). This is an interesting result, as it was concluded in Chapter 6 that behavioural control factors need to be improved to reduce the commitment-gap and stimulate more commitments. It therefore seems that improving the *Scrap_intensity* results in more commitments, as some of the companies that in the base case already had intention (but not enough control) now actually commit. The increase in commitments consequently results in more social pressure (i.e. subjective norm) for the firms that have not yet committed. As a result, more of these companies also develop intention, thereby keeping the commitment-gap almost constant while the number of commitments increases. Though Figure 6.3 portrayed that *Scrap_intensity* is on average higher among committed than non-committed firms, it was difficult to conclude from this figure alone that *Scrap_intensity* is an actually important driver of firm commitment. The results shown in Figure 7.2 indicate that the contextual factor of *Scrap_intensity* is an important influence in companies' commitment decisions. More generally this exploratory analysis shows that the factors relating to behavioural control limit the number of commitments.

Figure 7.2: Figures depicting the commitments and commitment-gap for the exploratory scrap intensity scenarios



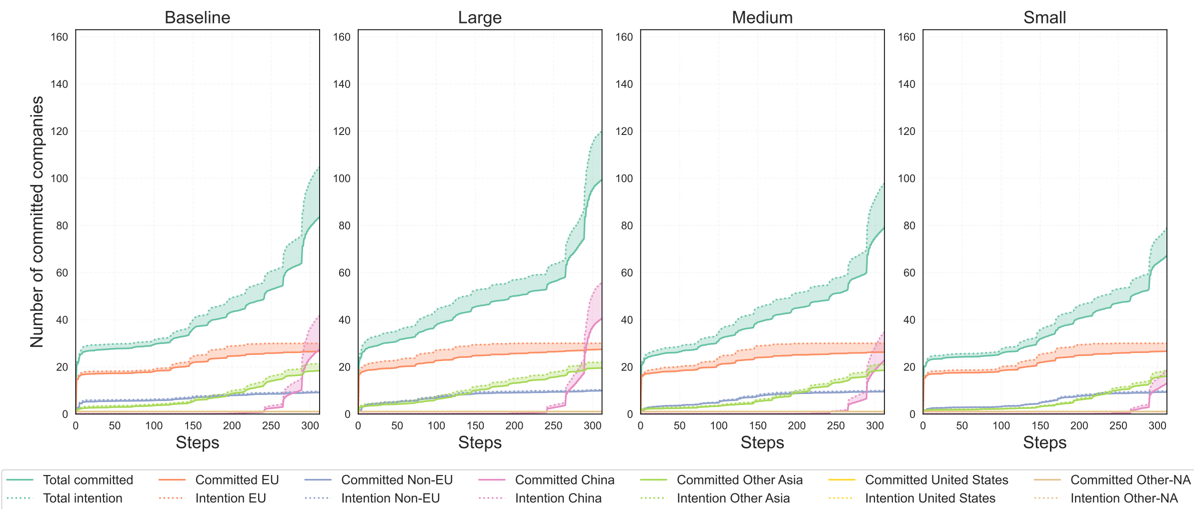
Exploratory size classification scenarios

Since the sensitivity analysis already showed that altering the size classification of the modelled companies can change the outcomes, it is logical that Figure 7.3 depicts noticeable changes between the scenarios. In the experiment where all companies qualify as large, the most companies commit. Though Figure 5.1 shows that a company's size negatively influences the perceived pressure of stakeholders on that company, this relation was modelled using absolute size numbers. Thus the size classification that was altered in these exploratory scenarios did not impact the influence of stakeholder pressure. On the other hand, size is also conceptualised to influence a firm's board diversity and number of members. These effects were modelled using a steelmaker's size classification, thus logically resulting in more commitments (or at least more companies with positive attitude) when all companies are 'large'.

Similarly, when all companies were simulated to be 'small', the model outputted fewer commitments. As Figure 7.3 shows, the drop in commitments (or rise in the 'Large' scenario) results mainly from the behaviour of Chinese companies. When all firms qualify as 'small', the number of committing Chinese firms does not even surpass the number of Other Asian committing firms. Considering that the commitment-gap in the 'Small' scenario is also much smaller than in the baseline scenario, the explanation for the lack in commitments could be that Chinese companies do not develop a positive attitude anymore when all classified as small. At least not within the modelled time-frame.

The scenario where all steelmakers are classified as 'Medium' most closely resembles the baseline. In this scenario, only slightly fewer commitments are made. Considering that both in the 'Medium' and 'Small' scenario there occur less commitments, a substantial part of the eventual commitments in 'Baseline' must come from 'large' companies. A similar conclusion was made in Section 6.2. Though the setting of size classification thresholds was a subjective process that thus influences the model's output, the changes are not significant enough to threaten the validity of the model with respect to inferring higher level patterns.

Figure 7.3: Figures depicting the commitments and commitment-gap for the exploratory size classification scenarios



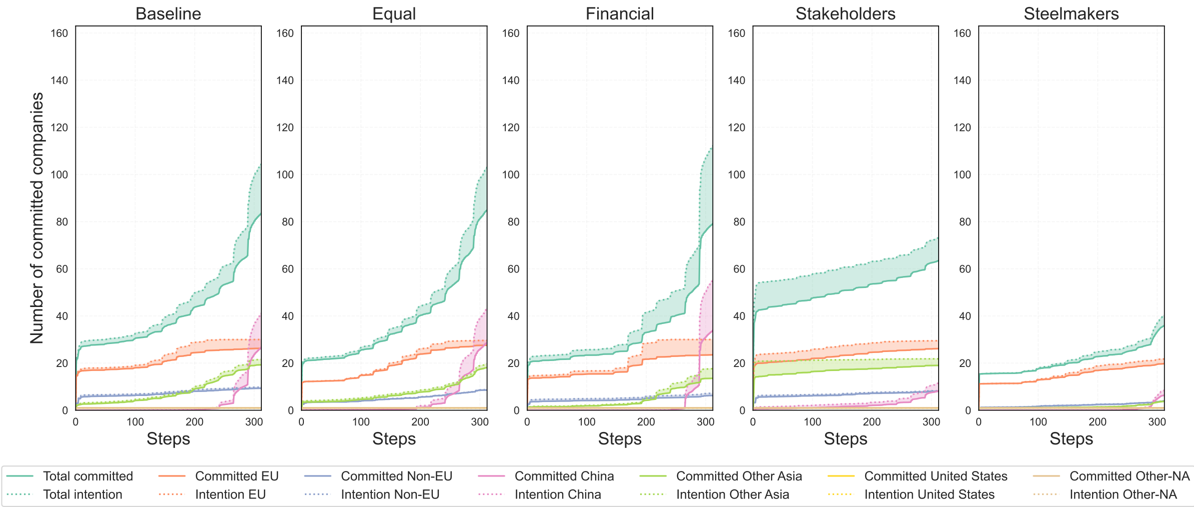
Exploratory weights scenarios

The last group of exploratory scenarios investigates to what extent the used weights influence the model output. They show what the effect would be if the steelmakers were focused on specific other factors than they are in the base case. As Figure 7.4 indicates, a scenario in which companies would give the same importance to all variables in a construct would result in very similar commitment levels as the baseline model. Interestingly, equal weights do result in smaller commitment-gaps for the different regions. Since the number of commitments per region stays approximately the same, it seems that this change must be caused by the different weights for the variables making up 'behavioural control'. As Table 5.4 shows, the only weight change that occurs for this construct in the Equal scenario is the shift in importance from *Financial_performance* to *Asset_age_opportunity*. The smaller commitment-gap can then be explained by the fact that *Asset_age_opportunity* is determined at the model start, immediately giving companies a higher score for 'behavioural control'[1]. Contrarily, *Financial_performance* is set

[1]That is, if they receive a high score for *Asset_age_opportunity*. However, all companies receive a score for *As-*

following a random process and the variable changes over time in both directions, therefore leading to more ambiguity as to how high 'behavioural control' will be.

Figure 7.4: Figures depicting the commitments and commitment-gap for the exploratory weights scenarios



In contrast to the Equal scenario, the commitment-gap does increase if companies focus more strongly on financial aspects. This is likely for two reasons. First, the exact opposite happens compared to the previously discussed scenario. Less importance is given to *Asset_age_opportunity*, while *Financial_performance* is valued more strongly. Moreover, the other two drivers of 'behavioural control' (*Scrap_intensity* and *Renew_electricity*) - which are both modelled to increase over time - also receive less weight, thereby likely further reducing companies' score for this construct. Secondly, much more emphasis is put on the perceived *Price_pressure* by companies. Similar to the baseline, the carbon price drives companies towards positive attitude at a moment when the control factors are not yet high enough for companies to actually commit. This once more shows that possible initiatives that aim to increase corporate climate action should not only emphasise aspects like carbon pricing, but should also focus on establishing actual decarbonisation opportunities for steelmakers.

In the Stakeholders experiment, steel companies have an extra focus on their owners and stakeholders. This emphasis leads to significantly different results. Not only do the numbers of committed companies differ, the way in which the commitment numbers develop over time are also substantially different. The fact that the number of commitments does not grow over time as much as in the previously discussed scenarios, is very likely due to the weight being put on two factors that are stable over the

set_age_opportunity of either 50 or 100. Since a company's score for *Financial_performance* can be anywhere between 0 and 100, it is likely that for many companies the *Asset_age_opportunity* score is higher than the value for *Financial_performance*.

course of the simulation. This simultaneously explains why the total and regional commitments increase significantly at once in the beginning. The lacking total number of commitments is on the other hand best explained by looking at the individual regions. Whereas most regions see similar commitment amounts, the Chinese companies commit substantially less in the Stakeholders experiment. This is explained through two factors. Firstly, carbon pricing, the normally strong commitment driver in China, receives only minor importance in this scenario. Secondly, the factors that do get more weight - *Ownership_pressure* and *Stakeholder_pressure* - are both dependent on the Environmental Performance Index of the country in which the steelmaker is located. Since China has the second lowest country-level EPI, Chinese companies score low on *Stakeholder_pressure*. Moreover, ownership was distributed among firms using numbers from La Porta et al. (1999), which indicates that approximately 80%-90% of companies in China are state-owned. As was explained in Section 3.3, state ownership in a low performing country with regards to the environment is not positive for a company's environmental stance. This was incorporated in the equation for *Ownership_pressure* (Equation (5.2)), now resulting in the inaction of Chinese companies. The outcomes of this scenario lead to the conclusion that pressure from stakeholders outside of the steel industry can have a significant impact on the behaviour of steelmakers. In order for such pressure to work most effectively, it is important that more awareness around the present environmental challenges is created in the countries where such awareness is currently low. By developing more awareness and improving the environmental stance of currently indifferent countries, the resulting up-rise of stakeholder interventions could potentially spur some of the most important corporations to action.

As was explained in Section 5.3, the last exploratory weights scenario alters the importance of general *Stakeholder_pressure* compared to the pressure exerted by other steelmakers. As such, this scenario models what happens if the companies are predominantly focused on *Competitor_commitment* and *Alliance_commitment* when determining social pressure. As the last plot in Figure 7.4 shows, such a change in weighting results in significantly fewer commitments. Altogether the total number of commitments is more than halved. Since it is mainly EU companies that are automatically committed from the model start (see Section 6.2 for elaboration), it is the number of commitments in this region that maintains the highest level. Moreover, as *Competitor_commitment* considers a company's continent, it follows logically that the initial EU commitments result in some spillover of behaviour to other - mostly EU - European firms. When studying China on the other hand, a counter-intuitive result is found. As was explained for the Stakeholders experiment, Chinese companies score low for *Stakeholder_pressure*. Now that the weights shift from this variable to *Competitor_commitment* and *Alliance_commitment*, it could be expected that more Chinese companies would commit. Instead the opposite holds true.

This is likely because there are only few early on commitments, which predominantly occur in the EU. As such, though *Stakeholder_pressure* receives less importance, the weights shift towards two variables for which the (Chinese) companies also score low. As was concluded in Section 6.2, in the base model companies perceive especially *Competitor_commitment* and *Stakeholder_pressure* as important. This was believed to be caused for a large part by the extra weight put on these variables. In contrast, the results from the Stakeholders and Steelmakers experiment indicate that, though the weights are important, other conditions still need to be in place for companies to commit. When it comes to *Stakeholder_pressure*, the right contextual factors are required so that pressure is actually exerted on steel companies. Whereas the Steelmakers scenario shows that there need to be other factors pushing an initial diverse group of companies towards climate action before the majority will follow, even when other companies' behaviour is modelled as very important.

7.2 Scenario results

Whereas in the previous sensitivity and exploratory experiments only one variable was varied at a time, this section presents the results of the testing of more comprehensive scenarios.

Carbon pricing scenarios

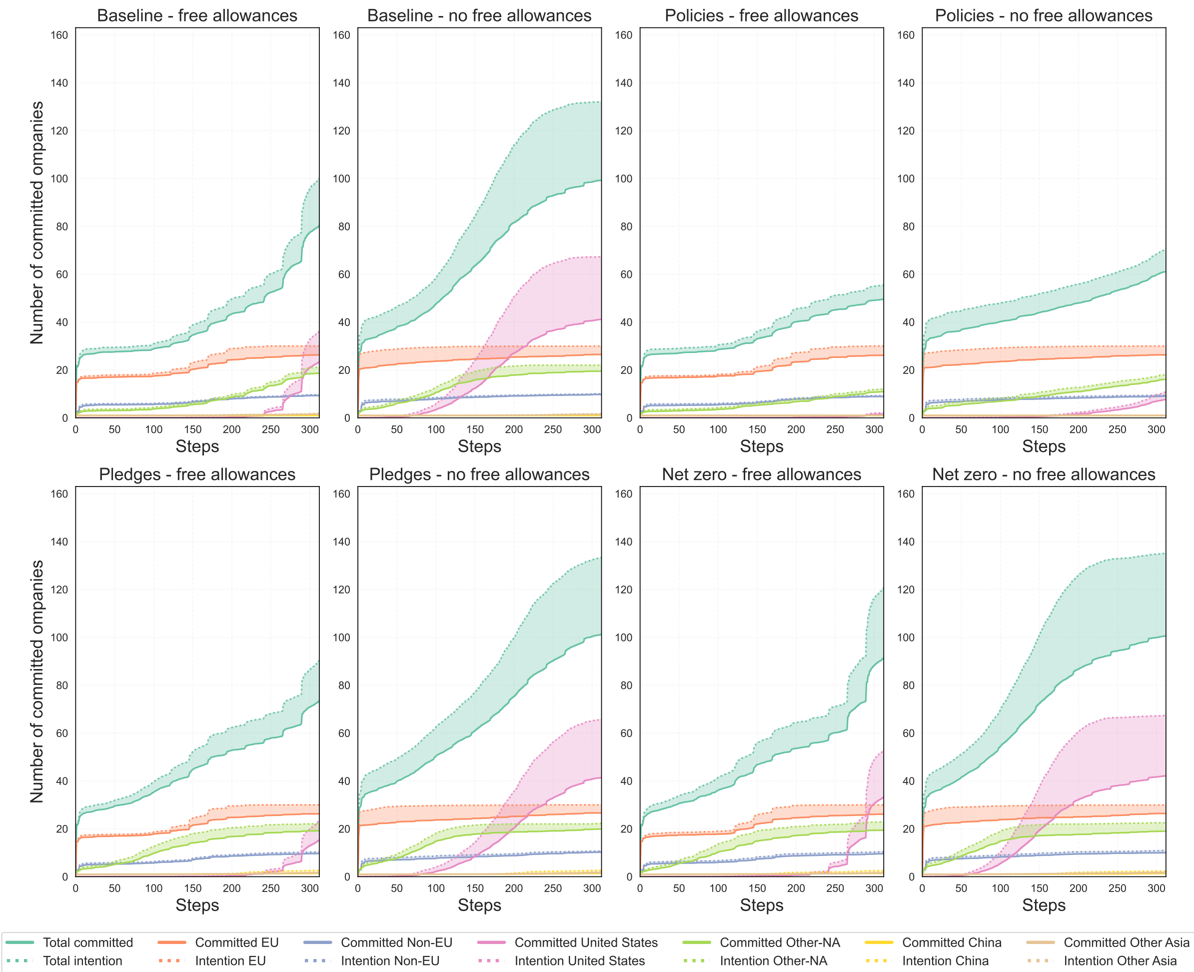
As the exploratory experiments and the analysis of the base model concluded that carbon pricing is an important aspect for companies in their decision-making, this scenario focuses explicitly on altering *Price_pressure*. More concretely, the pressure from carbon pricing is varied by changing either the *Carbon_price* per country, the number of *Free_allowances* companies receive, or both. Figure 7.5 depicts the impact of the modelled changes on the total number of commitments, the commitments per region and the commitment-gap. Firstly, it is interesting to note that by eliminating the distributed *Free_allowances* in the base model, many more commitments occur in the three regions that have at least one country with an ETS. However, not all intentions are translated into action, resulting in increasing commitment-gaps. This in general is an effect of removing *Free_allowances*, as it also occurs in the other scenarios.

Concerning both Policies scenarios, Figure 7.5 depicts that the eventual number of commitments is much lower than in the baseline case. In these scenarios, the same countries as in the base model are subject to a carbon price, though the programmed prices remain much lower in the Policies scenarios. This logically follows from the fact that the base scenario incorporates future expectations, while the Policies scenario only takes into account stated policies. Clearly the expectations of experts - as used as a source for the baseline - include future policies that are more ambitious.

Also more ambitious than current policy commitments are the emission reductions that countries have pledged to make. The IEA (2022b) estimated the necessary carbon prices to achieve these emission reductions, which were used in the Pledges scenarios. Interestingly, though all countries use a carbon price in these scenarios, the total number of commitments is still lower than in the base case. This likely follows from the modelled carbon price for China, which is lower in these scenarios than the price modelled in the baseline. Though the carbon prices in all other countries are higher in the Pledges scenario compared to the base scenario, the number of commitments remains lower due to the decarbonisation pledge - and corresponding carbon price - that is lacking behind for China. Moreover, when studying both the Pledges and Net Zero scenario without free allowances, it becomes clear that there is an approximate limit to the number of commitments that carbon pricing can stimulate. Similar to a conclusion made in Section 6.2, this allows to infer that more than just carbon pricing is needed to motivate adequate corporate climate action. Specifically, at a certain level, increased *Price_pressure* does not lead to more commitments, but instead results in a larger commitment-gap. Companies do thus not believe that the necessary behavioural control factors are already present. In other words, a large number of steelmakers lack a certain belief that they will actually be able to achieve science-based targets.

This also becomes clear when interpreting the number of total commitments in the 'Net zero - free allowances' scenario. The total number of commitments is only slightly higher than in the base case, even though the modelled carbon prices are higher for each country. As Figure 7.5 shows, however, at the simulation's end the commitment-gap rapidly increases, in line with the conclusion of the previous paragraph.

Figure 7.5: Figures depicting the commitments and commitment-gap for the carbon pricing scenarios



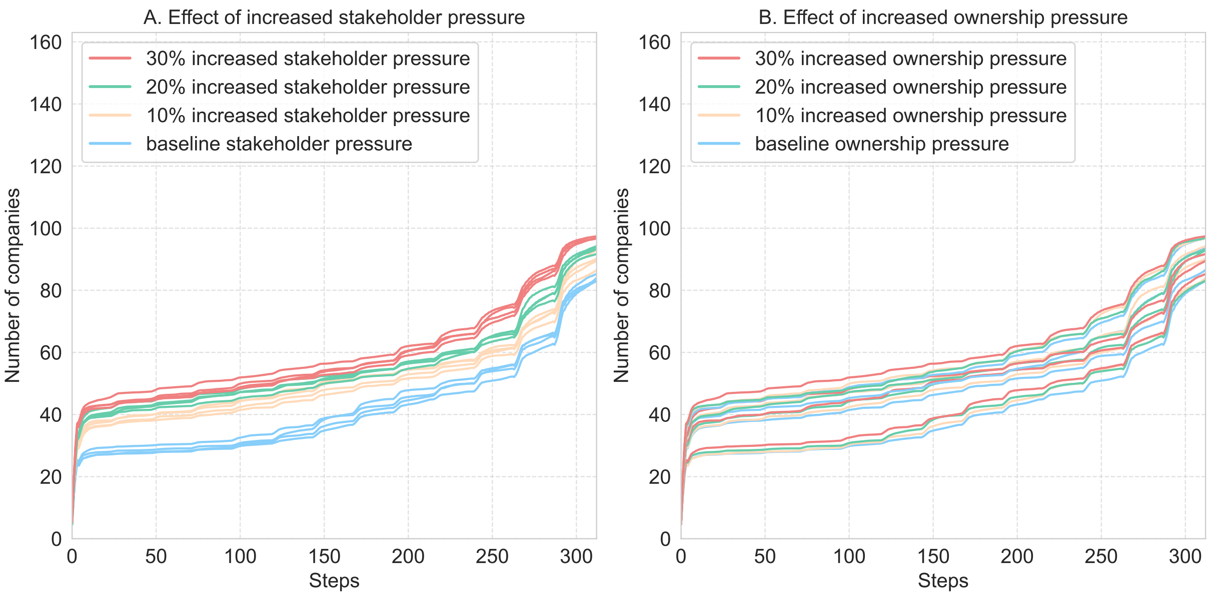
Stakeholder scenarios

In the Stakeholder scenarios, the *Stakeholder_pressure* and *Ownership_pressure* are altered. This is done to simulate a situation in which stakeholders are rallied by the SBTi to put pressure on steel companies. Figure 7.6 visualises the effect of increases in each of the changed variables. As is shown in Figure 7.6A, there is a very clear relation between the amount of *Stakeholder_pressure* the companies perceive, and the number of commitments. A similar correlation exists between the total amount of commitments and increases in *Ownership_pressure*. However, the mean number of commitments as portrayed in Figure 7.6B overlap more between scenarios[2] than those in Figure 7.6A. This signals that the effect of increasing *Stakeholder_pressure* is more substantial than the impact of changing *Ownership_pressure*.

[2]Where one scenario is the 'baseline' value for *Ownership_pressure*, another is *Ownership_pressure* increased by 10% compared to the baseline, and so on.

This could have multiple causes. For one, *Stakeholder_pressure* is weighted more heavily than *Ownership_pressure*, though both exist in a different TPB construct, making it challenging to accurately compare their weights. That *Stakeholder_pressure* is part of a company's 'subjective norm', whereas *Ownership_pressure* is used by companies in determining their attitude, could be another reason that the former seems more influential. Specifically, if companies in general more often commit based on a strong positive attitude instead of a very favourable subjective norm, altering the value of the latter has the potential to stimulate positive intentions among more companies[3]. As such, the results of this scenario show that it is worthwhile to focus especially on stakeholders other than the owners if the SBTi wants to effectively increase the number of commitments. However, it should be noted that the importance of each stakeholder group may vary per region and was not modelled as such. This possibility of more heterogeneous weighting is discussed further in Section 8.6.

Figure 7.6: Committed companies in the stakeholder scenarios, visualising the effect of variable changes



Each line represents the mean number of commitments over time. Both sub-figures show the same lines, though they are coloured differently. Each sub-figure visualises the effect of changing one of the two factors that are altered in the stakeholder scenarios. Every sub-figure therefore contains multiple lines of the same colour, as the variable represented in the other sub-figure is altered while holding the respective variable of the sub-figure at the value indicated by the line colour. For example, in sub-figure A the blue lines indicate that in these scenarios the stakeholder pressure is not changed compared to the baseline. The other factor is still varied - in this case taking one of four values - resulting in a total of 4 lines (i.e. variable combinations) when the stakeholder pressure is fixed at baseline level.

[3] Remember, a company develops intention if either 'attitude' or 'subjective norm' is *very high*, while the other should be *moderately high*. Based on previous findings, it seems like the strongest drivers for commitment is carbon pricing. This variable works on a company's attitude, thus likely leading to the fact that positive intentions are often developed based on a *very high* attitude. However, not all companies develop a sufficiently positive enough attitude so that it results in intention. For these companies, increasing the social pressure they perceive could be an effective way to still create intention. This phenomenon is referred to here, as raising the *Stakeholder_pressure* is a lever to increase a company's subjective norm

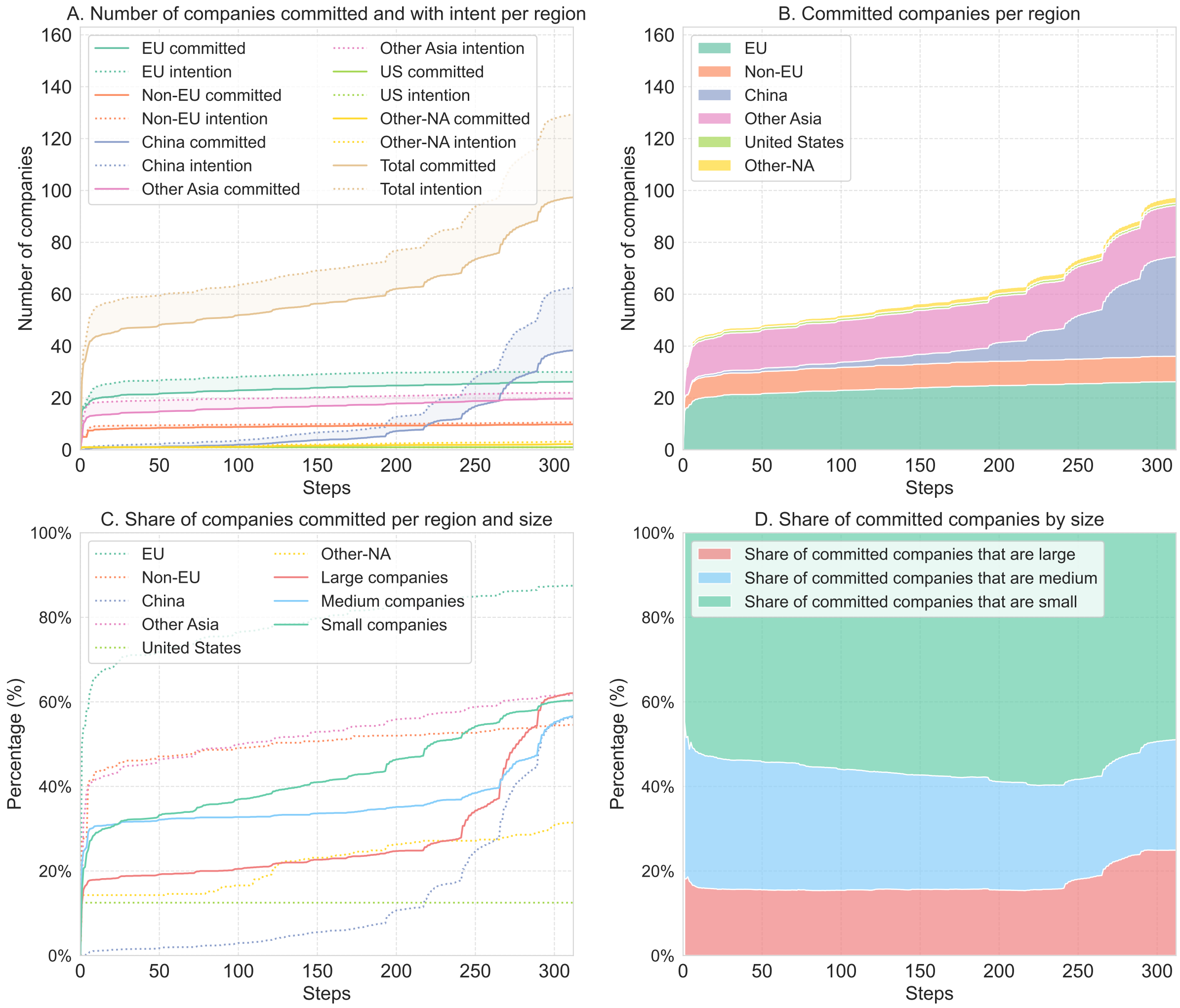
In order to further assess the modelled stakeholder scenarios, one specific scenario is singled out for comparison with the baseline. More concretely, the characteristics of the most 'extreme' - that is, leading to the highest number of commitments - is displayed in Figure 7.7. The figure shows that this specific stakeholder scenario results in more commitments and that the number of commitments rises more gradually than in the base case. This is primarily driven by earlier commitments in Other Asia and China (Figure 7.7B). The more gradual increase in commitments follows logically from two factors: i) the increased pressures modelled for this scenario result in companies earlier on developing intention and ii) apparently a large number of the companies that develop intention early on perceive the behavioural control as already sufficient. On top of the more gradual increase in commitments, it is noteworthy that increasing the *Stakeholder_pressure* and *Ownership_pressure* results in more activity in Other-NA (Figure 7.7C)[4]. The firms in this region are all either publicly listed or private and the EPI of both Canada and Mexico is not very high. As such, companies from Other-NA do in the base model in general not receive a high score for either *Stakeholder_pressure* or *Ownership_pressure*. The modelled increase in these variables in this stakeholder scenario therefore likely provides the edge that some of the companies in the region needed to develop intention. As such, ensuring that Canadian and Mexican companies feel more pressured by their stakeholders and owners can be a first step in stimulating more North American steel companies to set SBTs.

The fact that the number of commitments surpasses the base case is in line with findings of the exploratory weights scenarios (Stakeholders experiment), which concluded that outside stakeholder pressures can substantially influence steel companies' behaviour. However, that the amount of commitments rises early on in the simulations is noteworthy when taking into account that no factors relating to 'behavioural control' were varied. This entails that many of the modelled companies already perceive SBTs as achievable early on in the simulation. At first, this seems to contradict the findings of the carbon pricing scenario, which stated that a substantial amount of steel firms does not believe it can achieve potential SBTs. However, when studying the number of steelmakers that commit per region, it becomes clear that the total and regional commitment numbers in this stakeholder scenario still trail behind those in the carbon pricing scenario. In other words, the initial conclusions were made because there seemed to be somewhat of a limit to the number of companies that would commit within the time horizon of the simulation - even though there were plenty of companies with intention. From Figure 7.5 and Figure 7.7 it becomes clear that this invisible roof has not yet been reached in the most extreme stakeholder scenario. As such, it can be concluded that there are already a number of companies that are ready to commit if spurred to action by external parties. To reach also the companies that

[4]Note that this is hardly visible in Figure 7.7A as there are only very few companies from Other-NA in the model.

do not yet believe science-based emission reduction targets are realisable, focus should go towards the improvement of the decarbonisation possibilities.

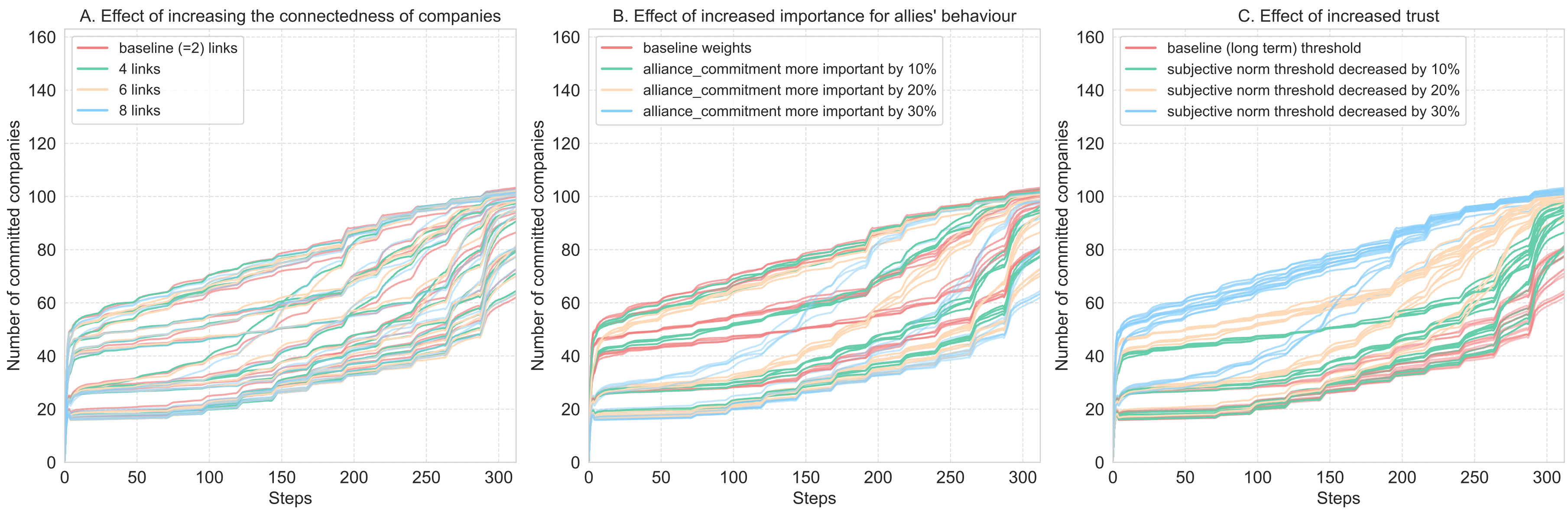
Figure 7.7: Figures depicting the stakeholder scenario where both the pressure from general stakeholders (*Stakeholder_pressure*) and that from owners (*Ownership_pressure*) is increased by 30% - the stakeholder scenario that results in the highest number of commitments



Network scenarios

In the network scenarios, the number of links companies are asked to create, the importance that steelmakers give to the behaviour of their allies and the threshold used to judge social pressure (i.e. the *Long_term_threshold* used specifically for 'subjective norm') are varied. The variations that are modelled are the hypothesised effects of organising working groups that aim to build connections and trust among the steel companies (see Section 5.3).

Figure 7.8: Committed companies in the network scenarios, visualizing the effect of variable changes



Each line represents the mean number of commitments over time. All three sub-figures show the same lines, though they are colored differently. Each sub-figure visualises the effect of changing one of the three factors that are altered in the network scenarios. Every sub-figure, therefore, contains multiple lines of the same color, as the variables represented in the other sub-figures are altered while holding the respective variable of the sub-figure at the value indicated by the line color. For example, in sub-figure C, the blue lines indicate that in these scenarios the threshold used for subjective norm is decreased by 30%. The other factors are still varied - in this case, both take one of four values - resulting in a total of 16 lines (i.e., variable combinations) when the subjective norm threshold is decreased by 30%.

The results of these parameter variations are presented in Figure 7.8. Figure 7.8C logically shows that decreasing the companies' *Long_term_threshold* for 'subjective norm' - a proxy for increasing their trust - is clearly inversely related to the number of commitments. That is, the more the threshold used for 'subjective norm' is reduced, the larger the number of commitments grows. On the other hand, Figure 7.8A shows a much less clear relation. Notably, the baseline value of two for *Create_links* results in both the highest and lowest number of commitments. In order to make sense of this, it is important to discuss what *Create_links* influences. If the companies are asked to create only few links, they will on average also only have few links. In such a case, a single committed ally could already put substantial pressure on the respective company (because *Alliance_commitment* incorporates the share of allies that are committed). However, since the company also has less allies, there is a lower probability that one of its allies is committed[5]. Vice versa, with more links, a company receives less pressure when one ally is committed, though the chance that at least one ally is committed is higher. That a value of two for *Create_links* then results in the lowest number of commitments, can likely be explained by the fact that this specific combination of parameter changes results in not the 'right' companies committing. More specifically, the companies that do commit are likely not linked to companies for which the *Alliance_commitment* increases sufficiently to develop intention. On the other hand, in the scenario where the social pressure threshold is lower, more firms commit, among whom likely also the 'right' companies. This finding is in line with the sensitivity of the model w.r.t. *Create_links* as identified in Section 6.3.

Figure 7.8B further shows that increasing the weight for *Alliance_commitment* does not necessarily lead to more commitments. More concretely, a combination of decreasing the *Long_term_threshold* (by 20% or 30%) and increasing the importance of *Alliance_commitment* (by 30%) results in later commitments. This is explained by the logic that early on other factors do not sufficiently stimulate commitment yet. Especially since weight is shifted from *Stakeholder_pressure* (can be high from model start) to *Alliance_commitment* (not high from model start if many companies are not immediately committed). As a consequence, allies do not yet pressure other allies and the increase in weight for *Alliance_commitment* adversely leads to fewer early commitments. Nonetheless, when other drivers grow strong enough to push more and more commitments, the increased focus of companies on what their allies are doing seems to result in a rapid diffusion of SBT commitment. This holds especially true for the scenarios where a high level of trust is built among the companies. In a way, it may be concluded that most companies are waiting for each other and do not have a strong drive to be one of the initial committers.

[5] Assuming that the total number of committed companies - in a given step - stays constant.

Figure 7.9: Figures depicting the network scenario with the baseline number of links, base importance for the behaviour of allies and a significant increase in trust - the combination that results in the highest number of links

Create_links = 2, Alliance_commitment weight is maintained at baseline level and Long_term_threshold is decreased by 30%

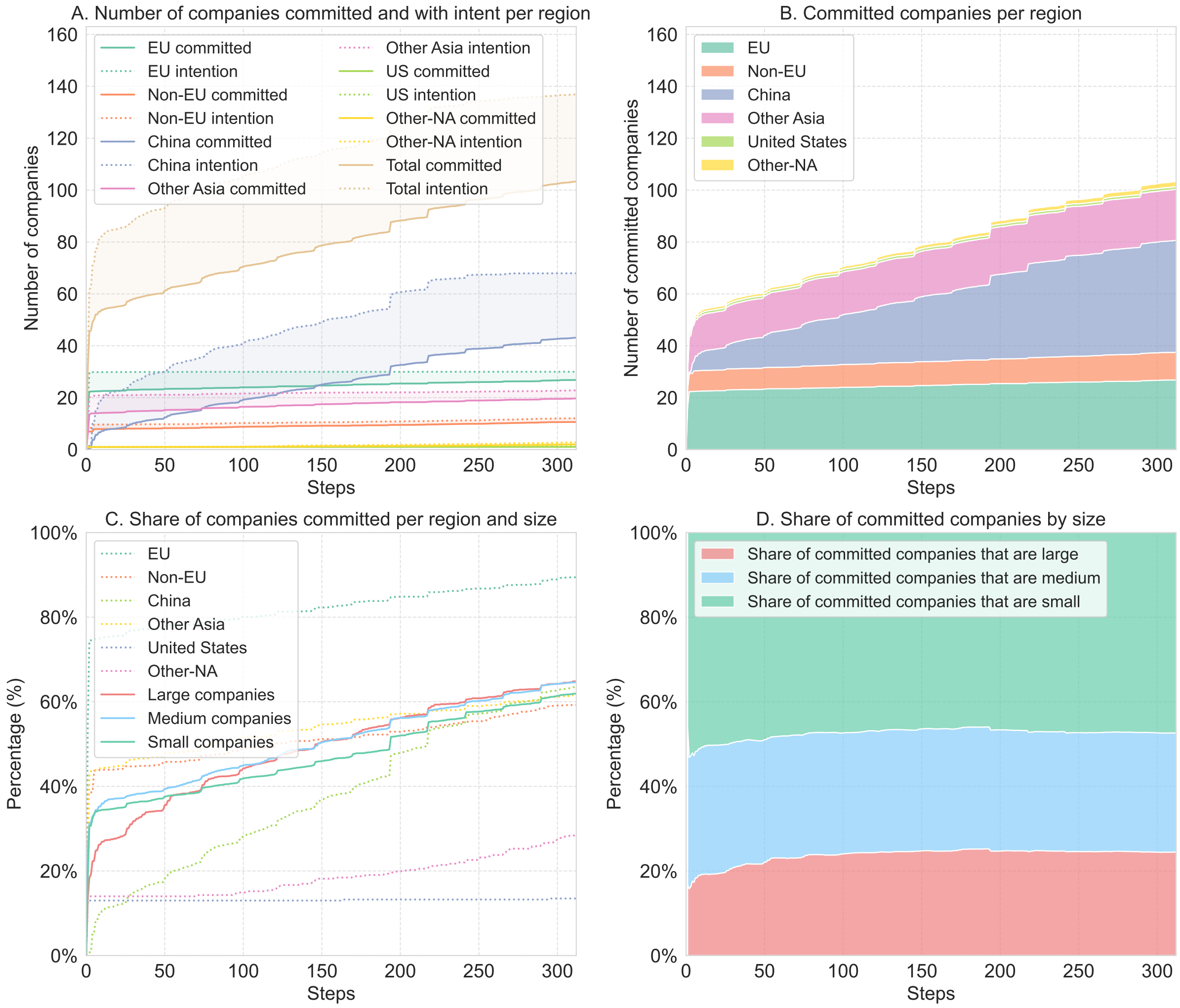


Figure 7.9 therefore displays in more detail what the effects are of building trust, as it depicts some system characteristics for the combination of parameter alterations that leads to the highest number of commitments. As Figure 7.9A & B show, building trust already early on results in more commitments on all continents. The positive perception of SBTs also spills over to regions where commitments in other scenarios have often been trailing behind, such as Other-NA (Figure 7.9C). Moreover, Figure 7.9D shows that companies of all sizes commit in this scenario. It thus seems that building trust results in wider support for SBT adoption among companies of all sizes. This can be relevant for reality, as in the real world small companies will possibly point towards the resources and inaction of the larger

steel firms in their justification for inaction. Simultaneously, it was identified in Section 3.3 that larger companies are more prone to fight pro climate pressure from stakeholders. To overcome these barriers, building trust appears to function as a catalyst for action among all types of companies.

Concluding from the observed system behaviour in the different scenarios, it seems that only increasing companies' focus on their allies does not result in more commitments. On the contrary, if this is the only action taken, the shift away from other factors may even result in fewer eventual commitments. Moreover, even when combined with other efforts, this change leads to companies committing later. Since limiting climate change is an urgent matter that requires substantial action as soon as possible, only increasing to what extent companies value their allies' and competitors' actions does not seem like an effective way to achieve this. On the other hand, providing steelmakers with a vision of what is possible regarding low-carbon steel in order to build trust can result in both more and earlier climate action. As identified before, there are still limits to the perceived attainability of SBTs. Consequently, even in a scenario with a high level of trust among steelmakers, the models shows that there exists a limit to the amount of company commitments. It should therefore once more be concluded that it is important to close the gap between intentions and commitments. In order to do this, appropriate efforts should go towards technological innovation, the roll-out of renewables and other factors that can provide steelmakers with a feeling of control over their decarbonisation trajectory.

7.3 Conclusion

This chapter has explored a number of scenarios in order to answer sub-question III: **What is the impact of different scenarios of company behaviour, stakeholder intervention and government stimulation on SBT adoption among companies?**

Running the exploratory experiments and scenarios has resulted in a number of interesting findings. Acknowledging the assumptions underlying the model, it can be inferred from the simulations that stakeholders substantially influence to what extent climate action is undertaken by companies. By increasing the pressure exerted by owners, financiers and other stakeholders, it was observed that SBT commitment in the steel industry spread to regions where there was previously not much activity. However, in order to most effectively encourage corporate sustainability, it is important that stakeholder groups first create more awareness and urgency with regard to the phenomenon of climate change in countries where the environment is not high on the agenda. Through such actions, stakeholder groups can push some first-movers towards increased climate efforts, as a large proportion of companies already sees SBTs as achievable. When this is done in combination with fostering increased cooperation and trust among the companies, the behaviour of the first-movers can diffuse rapidly. However, the results also indicate that there is some ceiling to the spread of climate action among companies. In order to break this invisible barrier, effort must go towards the improvement of decarbonisation options so that they become more (economically) viable. By improving the behavioural control factors, climate action can spread throughout the system as the companies assess what their peers do. Moreover, by developing more cooperation and trust, companies are shown to take action earlier on. This is of significant importance considering the urgency of climate change. In the same line, moving forward planned policies like carbon pricing can substantially increase the number of companies that have the intention to commit. If relevant stakeholder groups such as the SBTi, financial institutions and governments, find ways to appropriately cooperate they can establish the prerequisites on which the steel companies can work towards deep decarbonisation.

Chapter 8

Discussion & conclusions

This thesis set out to bring more understanding on the topic of target-based corporate climate action. In order to do so, an ABM was developed for three purposes: (i) provide **a proof of concept** that ABM can be useful to model companies' decision-making regarding target-based climate action, (ii) give initial **recommendations** on how companies can be stimulated to work towards deep decarbonisation and (iii) set up the **foundation for a transparent ABM** on which future academic work can build. This chapter will outline the contributions of this work towards each of these purposes. Firstly, the found results are compared to literature and real world patterns in Section 8.1. This is discussed to validate to what extent ABMs - in particular the one developed in this study - can represent real world CAS with companies focusing on target-based climate action. Consequently, the research questions are answered and recommendations are provided that translate the scientific outcome to concrete actions. Whereas the previous chapters and appendices form the basis for understanding the developed model, the limitations that future research can improve on are addressed at the end of this chapter.

8.1 Validating the use of agent-based modelling

Identified patterns are important system characteristics that can indicate to what extent a model's processes and structure are in line with reality (Grimm et al., 2005). This section therefore explores which of the results found are in line with previous literature or patterns that can be identified among committing companies in empirical contexts.

The most general real world trend that the model portrays is the growing number of companies that commit to setting SBTs over time (see for example Figure 4.2). Moreover, the model incorporates that commitments early on are most often made by European companies, as was previously determined by Giesekam et al. (2021). Nonetheless, personal communication with the SBTi's steel team led to the conclusion that companies believe that it is advantageous to be seen as a first-mover (Khan et al., 2023). Such a 'first-mover effect' was not incorporated in the model conceptualisation. Moreover, while the effect may occur in the real world, no such behaviour was explicitly found among the modelled companies. One explanation for this could be that the current market for green steel is not yet far enough developed, as low-carbon steel does not have a higher quality but is more costly to produce (Hermwille et al., 2022). Another clarification could be that (most of) the first-movers have already committed before 2023, whereas the companies that have not might care less about the social perception of being a front-runner and more about the contextual factors that enable deep decarbonisation.

This would be in line with the findings of the model, which suggest that certain socio-technological factors need to be present for most of the steel companies to take climate action. Once these factors are established at adequate levels and an initial group of firms commit, the modelled scenarios allow to infer that the majority of steelmakers is likely to follow. This behaviour aligns with the critical threshold that the SBTi believes is present when it concerns SBT adoption in an industry. Nonetheless, the necessity of adequate and (economically) viable decarbonisation options discredits the notion that increasing numbers of commitments among peers is enough to push a specific company to commit. As the SBTi steel team recognise themselves, "*companies will make sure they can fulfil the target reduction requirement before they make the commitment*" (Khan et al., 2023). This aligns with the conclusions of Hoffmann et al. (2020), which noted that, among others, high-quality scrap availability and access to low-carbon electricity are limiting factors for steel companies willing to take more climate action. That the model also found that these and the other behavioural control factors were limiting the number of commitments as in reality, suggests that the choice of using the Theory of Planned Behaviour was appropriate.

Interestingly, in the experiments with higher levels for some of the limiting factors, there were both direct and indirect effects on the number of commitments. Companies that already had the intention to set SBTs committed more often, while the connections between steelmakers then led indirectly to a neighbourhood effect and increased commitments. While not finding a critical threshold, the ABM was thus able to incorporate the contagious aspect of behaviour that the SBTi and Banda (2018) argued for. Moreover, that companies commit when for example renewables are more widely available - and therefore likely also cheaper - is in line with another conclusion of Khan et al. (2023). More specifically, the SBTi steel team suggests that financial cost-savings and (future) policies are important drivers for real companies to set SBTs. This is in accordance with the study's results, as firms are found to act with vigour when the cost of their operations increases due to carbon pricing.

An additional result that showed promising commitment numbers was the building of trust and cooperation among steelmakers. That such an approach could be worthwhile was similarly argued for by Hermwille et al. (2022), who propose that transnational cooperation can establish the prerequisites for a low-carbon steel industry. The CDP (2022a) further argue that exerting pressure on companies via financial institutions is more productive than when an initiative like the CDP or SBTi targets these companies directly. This effect was not explicitly included in the conceptualisation of the model. Though the pressure exerted by owners and financial institutions in the model was found to be important, no clear pattern was present in the output that allows to conclude that targeting (steel) companies via financial institutions is much more effective.

Altogether, the patterns found in the model output often overlap with the descriptions of the real system. Though ABMs are subject to limitations, the method makes it possible to explicitly include certain agent or system characteristics and therefore represent the CAS under study more accurately. Additionally, included lower level decision-making rules are able to give rise to system behaviour that matches with literature findings. In combination with the method's flexibility to simulate scenarios, this once more shows that agent-based modelling is an adequate tool to study CAS regarding target-based company climate action.

8.2 Answering the main research question

Overall the conclusions drawn in the previous section and chapters allow to formulate an answer for the defined research question. Though the individual sub-questions have briefly been answered in the previous chapters, they are once more discussed to formulate a comprehensive answer to the main research question.

Sub-question I: Which company and environmental characteristics are important for companies in their decision-making procedure regarding target-based climate action?

Since this thesis takes the steel industry as a case study, the decarbonisation possibilities of the steel sector were discussed first. By interpreting the relevant literature on low-carbon steel production, it was identified that technological factors such as low-carbon electricity availability, access to quality scrap metals and production capacity age are important for steelmakers when they consider decarbonisation. Additionally, a comprehensive literature review on the corporate drivers of environmental performance was conducted. The literature study has shown that company-specific characteristics such as financial liquidity, the demographics of the board of directors and a company's ownership are important drivers - or inhibitors - of a proactive stance towards mitigating climate change. On top of this, it was found that firms are influenced by contextual factors as well. Particularly, the pricing of emissions, behaviour of peers in the industry and influence of culture were deemed important. Stakeholders were further identified as influential, while it was also found that the size of a company generally determines the board demographics and influence of stakeholders to a certain extent.

For the purpose of structuring all the discovered relationships, the Theory of Planned Behaviour was appointed as an adequate behavioural theory based on which to model the decision-making process of companies. In order to do so, however, importance needed to be given to the various influential factors. This was done using another round of literature research, now specifically focused on the commitment of companies to the SBTi using, among others, Van Hilten (2022).

Sub-question II: How does the SBTi currently motivate companies to commit to science-based emission reduction targets through its operations?

In order to answer this question, the documentation available on the Science Based Targets initiative was studied. To get an understanding of the organisation's operations concerning the steel industry, contact was furthermore made with the SBTi's dedicated steel team. Altogether, the initiative is globally active and aims to involve businesses in the mitigation of significant climate change. Though the SBTi operates worldwide, they take a local approach to company engagement and focus first and foremost on the high-impact companies as defined by CDP. Together with the latter organisation, they also run a campaign that focuses on increasing the pressure on these high-impact companies through their supply chains and financial institutions. Moreover, by engaging in relevant events, the SBTi steel team aims to stimulate as many steelmakers as possible to set GHG emission reduction targets in line with the sector's decarbonisation pathway.

Sub-question III: What is the impact of different scenarios of company behaviour, stakeholder intervention and government stimulation on SBT adoption among companies?

While assessing the results of the various experiments and scenarios that were run, interesting findings were discovered. For example, it was found that stakeholders have the ability to increase the number of companies that have committed to setting SBTs. They can do this most effectively by first creating more awareness about the importance of limiting climate change in the regions where such awareness may presently be low. Different stakeholders will thus have differing roles to play in the transition of sectors towards a low-carbon norm. Owners and investors can for example push the companies that they are invested in to set credible emission reduction targets. On the other hand, environmental action groups can create the awareness that is needed, while particularly focusing on the regions where this is currently low. As a result, climate action is likely to become more discussed even in regions where there is currently not much action on the topic.

For environmental pro-activity to become a sector wide phenomenon however, all companies need to perceive the emission reduction that is necessary to limit global warming to 1.5℃ as achievable. The requirements for this are likely to differ substantially per industry and region. For steel specifically, it was found that limiting factors are for example the availability of scrap and renewable energy. Taking away the constraints for decarbonisation has been shown to have a double effect. Not only does it directly lead to more climate action, it also results in the norm within an industry shifting. The increased peer pressure from others taking action in turn influences more companies to do the same.

The spread of behaviour is especially strong when there is a higher level of trust and cooperation within a sector. As a result, sectors where this is prevalent will see both earlier climate action and a more rapid diffusion of the behaviour. Though climate action is sometimes seen as a competitive edge, the extent to which it is perceived as positive differs substantially per industry. Concerning the steel sector, greening production does not directly lead to any advantages in quality or cost (Hermwille et al., 2022). Only when the price of emission-intensive production becomes high enough, are companies more motivated to decrease their carbon footprint. Each industry will thus likely require a distinct approach to decarbonisation. By effectively aligning the actions of stakeholders, increasing and moving forward the regulations and policies limiting emissions and stimulating cooperation and trust, the companies in the most carbon intensive industries can be stimulated to take proper action.

How can companies be stimulated to commit to science-based greenhouse gas emission reduction targets as set by the SBTi?

By taking the number of commitments of companies to the SBTi as a quantifiable metric of climate action, this study set out to answer the above research question. In conclusion it has been shown that companies are influenced by a multitude of factors. Some of these factors are specific to each company, while others are dependent on contexts such as culture and location.

In order to create the conditions that result in increased climate action, all these factors are important. When companies lack the intention to reduce the emissions they produce, it is important to focus on the aspects that could alter this. In line with the literature review conducted to develop the model conceptualisation, carbon pricing is one of the most effective methods to change a company's attitude with respect to setting SBTs. However, the ABM also showed that carbon pricing and other drivers are not sufficient on their own. There exist important limiting factors that should be improved to create both direct and indirect positive effects on the number of commitments. As such, enhancing the access to limiting factors like high-quality scrap, low-carbon electricity and financial support can be an effective way to stimulate more climate action. Moreover, it should be acknowledged that the production capacity of committing companies in the model is considerably older than that of non-committing companies. Though this can be caused by other factors, it is possible that companies with older capacity feel a stronger urge to commit. The SBTi could therefore focus on these companies to build an initial base of committed steelmakers. Indirectly, this will result in increased peer-pressure and therefore commitments.

Additionally, as discussed previously, the SBTi is a well-connected initiative that could use this position to foster trust, cooperation and a more long term orientation in for example the steel industry. The scenario simulations in this study have shown that this could lead to earlier commitments. In combination with a specific focus on the companies with older steel-making capacity, the SBTi could therefore stimulate the urgent action that is necessary.

In complement to these actions of the SBTi, a number of other actions are needed. For example, more awareness and urgency surrounding the phenomenon of climate change has to be created in certain regions of the world. Moreover, the financial risk of deep decarbonisation should be reduced while opportunities should become more accessible. What roles specific stakeholders can play to establish increased company climate action is therefore discussed in the following section.

8.3 Recommendations

Interpreting the findings and conclusions of this study, a number of relevant recommendations can be made.

For the **SBTi** it seems that, in addition to its current engagement strategies, the initiative can play an important role in connecting different stakeholder groups. As the organisation already organises workshops in which experts, NGOs, companies and other parties come together, it could use its position as the connector of these groups to foster more collaboration between stakeholders. Moreover, since representatives of the initiative already participate in sector-related events, they can use their extensive networks to encourage cooperation among the companies in an industry - be it steel, cement or any other sector. The SBTi could for example do this by organising EAG-like workshops in which a variety of companies in a sector develop a shared vision and set guidelines for a collaborative decarbonisation approach. As was shown, many different stakeholders are needed to decarbonise the most emission-intensive industries. The SBTi has formulated relationships with many of these actors since its inception. Managing the needs of different stakeholders is challenging when the societal system transitions towards a new, low-carbon, status quo. It is therefore recommended that the SBTi uses its relationships and position in business networks to align the needs and actions of all stakeholders with the scientific consensus of what is necessary climate action. In addition, the initiative is advised to focus its efforts on those companies that are most likely to commit. In essence this includes the companies for which adequate decarbonisation is a possibility. The findings of this study suggest that these are the companies with older production assets, substantial financial liquidity and/or sufficient access to scrap and renewables.

Regarding **governmental agencies**, it has been shown that policies can have far-reaching consequences. Through the global interconnectedness of stakeholders and companies, even regional governments can have global impacts. One concrete example of this is the introduction of a Carbon Border Adjustment Mechanism (CBAM) by the European Union. This particular mechanism is useful to put financial pressure on large GHG emitters, regardless of where they operate. As was found, such carbon pricing related policies can substantially increase the climate action of companies. However, policies like the CBAM only spread the pressure from carbon pricing to a certain extent. Governmental agencies in regions where carbon pricing is not yet introduced are therefore recommended to introduce this and other climate policies as soon as possible. Considering the urgency of climate change, those regions where carbon pricing has already been introduced are moreover advised to increase the financial pressure put on high emitting companies. This can be done by sooner phasing out free emission allowances or more quickly raising minimal carbon pricing levels. Additionally, governments are advised to assess what the limiting factors of decarbonisation in the most emission-intensive industries are and how they can progress the availability of these factors.

Lastly, a variety of important roles can be played by other stakeholder groups. Either by joining the CDP-SBTi campaign or by other ways of pro-climate engagement, **financial institutions** can stimulate the largest companies in the world to take action. Moreover, it is suggested that these organisations increase the amount of money they allocate towards green investments. Considering that financial liquidity and risk are often barriers to investing in low-carbon solutions, making more money available for such initiatives is crucial. In their role as **owners**, financial institutions but also other parties can vote in favour of climate resolutions at the annual shareholder meetings of the companies they are invested in. Moreover, they can engage in dialogues with the board of companies to show that they do not only care about short-term financial returns. Since climate change and future policies will result in stranded assets in the most emitting industries, pushing for climate action is also in their own best long-term interest. However, financial institutions, owners, governmental agencies and other stakeholder groups do not always and everywhere value environmental action the same way. It is therefore important that **environment action groups** and **scientists** continue to create awareness about the urgency of climate change. To stimulate hope rather than despair, dialogues between these and other stakeholders should also be focused on the solutions and roles of different parties. That way, all stakeholders can be effectively motivated to work towards a net zero society.

8.4 Societal contribution

In line with Bornmann (2013), academic research can contribute to society in one or more of four domains. The value of this study to these dimensions is discussed in this section.

Social and cultural contribution

Mitigating climate change is a challenge that requires global attention and action. As was discussed in Chapter 1, the way in which global warming has until now been managed is inadequate. There is therefore a need to shift the burden of emission reduction towards the organisations that are responsible for a large share of anthropogenic GHG emissions. The results of this study can be used to inform the societal debate on how to stimulate these corporations to decarbonise. Although the model is specific to the steel industry, findings can carefully be generalised to other emission-intensive sectors. Moreover, the developed ABM lays the foundation for future models that can be applied to a variety of industries and regions. By shifting the scope, the model can be used to inform policy-making on both the international and local level. Altogether, it allows the SBTi and other ICIs to more effectively stimulate climate change mitigation with corporate players. The results of this and future models can furthermore be used to effectively coordinate the efforts of other stakeholders.

Since emitting GHGs has global results it is important to bring more understanding of the behaviour of emitters in all regions. Though this study has only focused on the Northern Hemisphere, it has incorporated companies in upcoming economies in Asia. The results of this study therefore provide an idea of how to motivate emitting firms to decarbonise in both developed and developing regions. In future iterations of the ABM, it is worthwhile if the countries in the Global South are also modelled. Not only will it be developing regions that feel the repercussions of climate change the most, it is also the still developing countries that will in a business-as-usual scenario strongly increase their emissions in the coming decades. Since much of the potential emissions of these regions are in the future, the model can be used to devise effective policies and company engagement efforts so that these emissions are avoided.

Environmental contribution

This study provides an environmental contribution in a number of ways. First of all, by stimulating companies to take climate action, the amount of released GHGs is reduced. This work focused specifically on the steel industry, which is responsible for approximately 8% of anthropogenic emissions (WorldSteel, 2021a). However, it is probable that the policy and engagement methods useful in the steel industry are also applicable to other emission-intensive industries. Though companies in other sectors that are less emission-intensive likely behave differently, the model can be expanded in future iterations to enhance its representativeness of such sectors. Thereby, it can be used to motivate emission reduction efforts among other types of companies. Moreover, the developed ABM provides a blueprint for future models that can be used in developing regions. As was explained previously, emissions in these regions could therefore be evaded. Lastly, the model can be applied to cover other environmental challenges such as biodiversity. The Science Based Targets Network (2023) has recently released the first set of 'science-based targets for nature', enabling companies to monitor and reduce their impact on water and land. By using this study as a foundation, a novel iteration of the model could be developed to assess the best way in which to stimulate corporate action for (for example) biodiversity.

Economic contribution

The economic contribution of this work comes from its relevance for effective policy-making and strategy development. Regarding the former, governmental bodies can simulate numerous policy scenarios using the developed ABM. In doing so, it is possible to assess which policies are most effective to stimulate climate action among businesses. This information then needs to be combined with cost aspects, to outline which policies are financially most efficient. On a more indirect level, it may also be argued that larger emission reductions will result in less economic damages from climate change. Considering the second point - effective strategy development - the findings of this ABM and future iterations can be useful for the SBTi and other ICIs to allocate their resources. Using the model, the initiatives can assess which strategic actions are most worthwhile to pursue and allocate their scarce resources accordingly.

8.5 Reflections

Reflecting on the development and implementation of the agent-based model, a number of choices could have been made differently, potentially leading to different results. Most prominently, the number of commitments to the SBTi was defined as an adequate quantifiable metric for climate action among firms. While still focusing on companies joining the SBTi, it could also have been decided to track the number of companies that actually set targets. Instead, it was decided that the phase up to commitment and that after are two distinct processes, of which this study focuses on the former. Nonetheless, the fact that companies have the ability to drop their commitment could have wider repercussions for the total number of commitments. Companies that remove their commitment for example do not exert peer pressure anymore, with the consequence that other companies perceive less stimulation to commit.

Moreover, the choice to take the steel industry as case may also have resulted in particular outcomes that are only applicable to the steel industry - or potentially other emission-intensive industries. For example the behavioural control factors may not have been as limiting for companies in other industries and carbon pricing, one of the main drivers for commitment, is not used in all sectors. Moreover, the choice for a case study of the steel industry resulted in a particular focus on the continents in the Northern Hemisphere. Countries and regions that were not included have different cultures, contextual settings and perceptions of climate action that are now not included in the model. Generalising the findings to such places should therefore be done with care.

Concerning the countries that were modelled, it is also important to note that all exports and imports were considered beyond the scope of this study. Including these would, however, change to what extent companies have access to scrap or are subject to a carbon price (through CBAM) in different parts of the world. This may have led to different results when comparing companies from the various regions, particularly as carbon pricing is a main driver while scrap availability is an important limiting factor for steel companies' climate action. The weighting of the variables is another factor that may warrant a more local approach than was used in this work. Providing different weights to companies based on their location, size, demographics and other characteristics could give an even more clear insight on how to approach different types of companies.

Two other decisions regard the inclusion of the current focus of the SBTi on specific companies. First of all, the initiative targets so-called high-impact companies, and these are characterised by the fact that they are publicly listed. In the current model, it has not been incorporated that there is a specific focus by the SBTi on listed firms. Including this effect would have likely led to different characteristics of the committing group of companies, though how it would have changed is hard to determine since the system under study is a CAS. The second choice concerns the splitting of companies, which was done to ensure more accuracy in which market a company serves and where it produces. However, the splitting also resulted in - 'fictional' - regional subsidiaries for some of the largest companies, whereas the SBTi stimulates the parent companies to set targets. Moreover, since size is an important characteristic within the model, the splitting may have impacted the representativeness of the model for the chosen population.

Lastly, it is important to reflect on the use of available data in the model. For instance, the Environmental performance Index scores were taken from 2022 and assumed stable over the modelled time horizon. In reality, the EPI score of a country varies from year to year. However, new aspects are included in the EPI calculations on a regular basis. This made it difficult to establish a trend, which could be used to adequately model future environmental performance. That countries' stance towards environmental action changes over time is nonetheless a fact. Including the EPI in a dynamic way, could thus have influenced the model results. Similarly, the cultural dimensions used in this work were assumed constant. As Beugelsdijk et al. (2013) argue, though the relative cultural position of countries remains stable over time, the actual Hofstede values of countries do change. Incorporating cultural changes over the time horizon of the simulation may thus have led to different findings.

8.6 Limitations & future research

The found results and developed agent-based model are subject to a number of limitations. For instance, the technological side of decarbonisation and increasing viability of low-carbon technologies is in the ABM proxied by the availability of renewables and scrap. Other factors that may be important as argued for by IEA (2020) are for example the current technologies of steel companies and possibility for efficiency improvements in current capacity. These factors could not be included due to data and time constraints, however, future research should focus on including these and potentially other important factors as they would influence companies' perceived behavioural control. Since one of the important findings of this study is that the modelled behavioural control factors limit companies' target-based climate action, including other relevant drivers and inhibitors may show novel emergent patterns. In line with this, future research should include emissions-data for companies so that other decision-making processes, such as cost-benefit analysis, can be modelled. Recently, two papers in Nature (Lei et al., 2023) and Nature Climate Change Xu et al. (2023) were published that could help in incorporating emissions-data on the plant-level in future versions of the developed agents based model.

Additionally, a number of the incorporated company characteristics built on non-industry-specific data. To draw more precise conclusions for specific industries, it is important that future models incorporate the most accurate data available. For example, this study used diversity and board age scores that were specific to the country in which a company is headquartered. For an industry like steel it seems plausible that diversity and board age were therefore overestimated. Another limitation regarding the modelled variables concerns their weighting. In the developed ABM, all companies weight the drivers and barriers the same. It is, however, likely that companies in China find other drivers important than those in Mexico. In addition, future iterations of the developed ABM could include other factors that represent what companies find important. For example, it may be that companies put most emphasis on the behaviour of competitors in the same country, whereas they value the actions of peers on the same continent to a lesser extent. In the ABM of this work, differences in companies' focus were to a certain extent incorporated by including countries' Environmental Performance Index and cultural contexts. However, future research should emphasise heterogeneity regarding the weighting of variables. As a result, more detailed conclusions can be made for companies in specific regions.

Future research should also look into companies that fell outside of the scope of this study. More specifically, the OECD (2023) notes that small-and-medium-sized enterprises make up a large share of the total number of steel producing companies while they were not explicitly modelled. Moreover, by modelling other industries than steel, it can be concluded with more certainty if the findings of this study also apply to non-steel companies. Studying the climate action behaviour of companies in other emission-intensive sectors may help to understand if the identified commitment patterns are more widely applicable to other types of heavy industry that need to decarbonise rapidly in order to achieve a limit of 1.5℃ warming. Additionally, the dynamics among companies in other industries may influence company behaviour in (for example) the steel sector. By modelling supply-chain linkages, behavioural spillover effects between industries could be modelled and studied.

Considering the results of the conducted OFAT sensitivity analysis, it was found that the model is particularly sensitive to a number of parameters. Varying the threshold used to classify companies as medium-sized resulted in noticeable differences in the model output. Per studied sector, it should thus be clearly defined when companies qualify as small, medium or large. Moreover, the agent-based model was found to be sensitive to alterations in the effect with which a company's size influences that same company's board size. That this relation exists was proven by previous academic work, though future research should more clearly identify the size of the found effect, preferably making distinctions for different sectors or types of companies. What should also be quantified on a country-level is from which carbon price level onwards low-carbon solutions become more favourable. This study used a conservative estimate based on findings for Germany. However, as was discussed in Section 5.3, substantial differences exist between the German and other economies that warrant more research on this topic. The sensitivity analysis further found that varying the *Threshold_mp* resulted in strongly different results. Identifying to what extent companies incorporate their long term orientation in their strategic decision-making is therefore an important next step for modelling ABMs with companies. Moreover, since Den Hartigh et al. (2005) found that business ecosystem networks are important, more research should go towards defining the networks in which companies operate. On top of all this, a comprehensive global sensitivity analysis should be conducted in order to more accurately examine the effects of varying multiple factors at the same time (Ten Broeke et al., 2016).

References

Arens, M. (2016). "Technological change and industrial energy efficiency: Exploring the low-carbon transformation of the German iron and steel industry". Ph.D. dissertation. Copernicus Institute, Utrecht University.

Arens, M., M. Åhman, and V. Vogl (2021). "Which countries are prepared to green their coal-based steel industry with electricity?-Reviewing climate and energy policy as well as the implementation of renewable electricity". In: *Renewable and Sustainable Energy Reviews* 143, p. 110938.

Arens, M., E. Worrell, and W. Eichhammer (2017). "Drivers and barriers to the diffusion of energy-efficient technologies—A plant-level analysis of the German steel industry". In: *Energy Efficiency* 10, pp. 441–457.

Arnegger, M., C. Hofmann, K. Pull, and K. Vetter (2014). "Firm size and board diversity". In: *Journal of Management & Governance* 18, pp. 1109–1135.

Arvitrida, N., A. Tako, D. Robertson, and S. Robinson (2017). "Duration of collaboration from a market perspective: An agent-based modeling approach". In: *Operations and Supply Chain Management: An International Journal* 10.3, pp. 149–159.

Azjen, I. (2019). *Theory of Planned Behavior Diagram.* URL: https://people.umass.edu/aizen/tpb.diag.html.

Balci, O. (1994). "Validation, verification, and testing techniques throughout the life cycle of a simulation study". In: *Annals of operations research* 53, pp. 121–173.

Balke, T. and N. Gilbert (2014). "How do agents make decisions? A survey". In: *Journal of Artificial Societies and Social Simulation* 17.4, p. 13.

Banda, M. L. (2018). "The bottom-up alternative: the mitigation potential of private climate governance after the Paris Agreement". In: *Harv. Envtl. L. Rev.* 42, p. 325.

Banerjee, R., Y. Cong, D. Gielen, G. Jannuzzi, F. Maréchal, A. McKane, M. Rosen, D. van Es, and E. Worrell (2012). "Chapter 8, End-Use Efficiency: Industry". In: *Global energy assessment: toward a sustainable future*, pp. 513–573.

Baptista, L. B., R. Schaeffer, H. L. van Soest, P. Fragkos, P. R. Rochedo, D. van Vuuren, R. G. Dewi, G. Iyer, K. Jiang, M. Kannavou, et al. (2022). "Good practice policies to bridge the emissions gap in key countries". In: *Global Environmental Change* 73, p. 102472.

Barbier, E. B., J. C. Burgess, and T. J. Dean (2018). "How to pay for saving biodiversity". In: *Science* 360.6388, pp. 486–488.

Bataille, C., S. Stiebert, and F. Li (2021). *GLOBAL FACILITY LEVEL NET-ZERO STEEL PATHWAYS: TECHNICAL REPORT ON THE FIRST SCENARIOS OF THE NET-ZERO STEEL PROJECT.* Tech. rep. URL: http://netzerosteel.org/wp-content/uploads/pdf/net_zero_steel_report.pdf (visited on 04/11/2023).

Beugelsdijk, S., R. Maseland, and A. van Hoorn (2013). "Are Hofstede's culture dimensions stable over time? A generational cohort analysis". In: *A Generational Cohort Analysis (October 7, 2013).*

Bjørn, A., J. P. Tilsted, A. Addas, and S. M. Lloyd (2022). "Can science-based targets make the private sector Paris-aligned? A review of the emerging evidence". In: *Current climate change reports* 8.2, pp. 53–69.

Boone, A. L., L. C. Field, J. M. Karpoff, and C. G. Raheja (2007). "The determinants of corporate board size and composition: An empirical analysis". In: *Journal of financial Economics* 85.1, pp. 66–101.

Bornmann, L. (2013). "What is societal impact of research and how can it be assessed? A literature survey". In: *Journal of the American Society for information science and technology* 64.2, pp. 217–233.

Bosnjak, M., I. Azjen, and P. Schmidt (2020). "The theory of planned behavior: Selected recent advances and applications". In: *Europe's Journal of Psychology* 16.3, p. 352.

Bowen, F. E. (2002). "Does size matter? Organizational slack and visibility as alternative explanations for environmental responsiveness". In: *Business & Society* 41.1, pp. 118–124.

California ARB (2020). *GHG Emission Inventory Graphs.* URL: https://ww2.arb.ca.gov/ghg-inventory-graphs (visited on 05/02/2023).

Calza, F., G. Profumo, and I. Tutore (2016). "Corporate ownership and environmental proactivity". In: *Business Strategy and the Environment* 25.6, pp. 369–389.

Castro, J., S. Drews, F. Exadaktylos, J. Foramitti, F. Klein, T. Konc, I. Savin, and J. van den Bergh (2020). "A review of agent-based modeling of climate-energy policy". In: *Wiley Interdisciplinary Reviews: Climate Change* 11.4, e647.

CDP (2022a). *CDP Science-Based Targets Campaign Final Progress Report: 2021-2022 campaign.* Tech. rep. URL: https://www.cdp.net/en/investor/engage-with-companies/cdp-science-based-targets-campaign.

— (2022b). *CDP's Activity Classification System (CDP-ACS).* Tech. rep. URL: https://cdn.cdp.net/cdp-production/cms/guidance_docs/pdfs/000/001/540/original/CDP-ACS-full-list-of-classifications.pdf (visited on 03/04/2023).

Chan, B. (2022). *Scaling up steel industry climate actions through science-based targets.* URL: https://sciencebasedtargets.org/blog/scaling-up-steel-industry-climate-actions-through-science-based-targets (visited on 02/01/2023).

Chen, T. (2015). "Institutions, board structure, and corporate performance: Evidence from Chinese firms". In: *Journal of Corporate Finance* 32, pp. 217–237.

Chernykh, L. (2008). "Ultimate ownership and control in Russia". In: *Journal of Financial Economics* 88.1, pp. 169–192.

Coles, J. L., N. D. Daniel, and L. Naveen (2008). "Boards: Does one size fit all?" In: *Journal of financial economics* 87.2, pp. 329–356.

Commission, E. (2014). *Horizon 2020 Work Programme 2014-2015: General Annexes.* Tech. rep. URL: https://ec.europa.eu/research/participants/data/ref/h2020/wp/2014_2015/annexes/h2020-wp1415-%20annex-ga_en.pdf (visited on 04/16/2023).

Constantino, S., M. Schlüter, E. U. Weber, and N. Wijermans (2021). "Cognition and behavior in context: a framework and theories to explain natural resource use decisions in social-ecological systems". In: *Sustainability Science* 16.5, pp. 1651–1671.

Craig, J. and C. Dibrell (2006). "The natural environment, innovation, and firm performance: A comparative study". In: *Family business review* 19.4, pp. 275–288.

Darnall, N., I. Henriques, and P. Sadorsky (2010). "Adopting proactive environmental strategy: The influence of stakeholders and firm size". In: *Journal of management studies* 47.6, pp. 1072–1094.

De Beer, J., E. Worrell, and K. Blok (1998). "Future technologies for energy-efficient iron and steel making". In: *Annual review of energy and the environment* 23.1, pp. 123–205.

De Villiers, C., V. Naiker, and C. J. Van Staden (2011). "The effect of board characteristics on firm environmental performance". In: *Journal of Management* 37.6, pp. 1636–1663.

Dekker, J. and T. Hasso (2016). "Environmental performance focus in private family firms: The role of social embeddedness". In: *Journal of Business Ethics* 136, pp. 293–309.

Deloitte (2015). *Women in the boardroom: A global perspective - 4th edition*. Tech. rep. URL: https://www2.deloitte.com/in/en/pages/risk/articles/women-in-the-boardroom-a-global-perspective.html (visited on 05/20/2023).

— (2017). *Women in the boardroom: A global perspective - 5th edition*. Tech. rep. URL: https://www2.deloitte.com/xe/en/pages/risk/articles/women-in-the-boardroom5th-edition.html (visited on 05/20/2023).

— (2019). *Women in the boardroom: A global perspective - 6th edition*. Tech. rep. URL: https://www2.deloitte.com/us/en/pages/risk/articles/women-in-the-boardroom-global-perspective.html (visited on 05/20/2023).

— (2021). *Women in the boardroom: A global perspective - 7th edition*. Tech. rep. URL: https://www2.deloitte.com/ua/en/pages/risk/articles/women-in-the-boardroom-a-global-perspective-seventh-edition.html (visited on 05/20/2023).

Den Hartigh, E., M. Tol, J. Wei, W. Visscher, and M. Zhao (2005). "Modeling a business ecosystem: An agent-based simulation". In: *Fifth annual meeting of the european chaos and complexity in organisations network ECCON*.

Dignum, F., V. Dignum, and C. M. Jonker (2009). "Towards agents for policy making". In: *Multi-Agent-Based Simulation IX: International Workshop, MABS 2008, Estoril, Portugal, May 12-13, 2008, Revised Selected Papers 9*. Springer, pp. 141–153.

Dyck, A., K. V. Lins, L. Roth, and H. F. Wagner (2019). "Do institutional investors drive corporate social responsibility? International evidence". In: *Journal of financial economics* 131.3, pp. 693–714.

Earnhart, D. and L. Lizal (2006). "Effects of ownership and financial performance on corporate environmental performance". In: *Journal of Comparative Economics* 34.1, pp. 111–129.

Edmonds, B. (2017). "Different modelling purposes". In: *Simulating social complexity: A handbook*, pp. 39–58.

Ember (n.d.). *Carbon Price Tracker*. URL: https://ember-climate.org/data/data-tools/carbon-price-viewer/ (visited on 04/09/2023).

Epstein, J. M. (2006). "Remarks on the foundations of agent-based generative social science". In: *Handbook of computational economics* 2, pp. 1585–1604.

Eurofer (2022). *European Steel in Figures*. Tech. rep. URL: https://www.eurofer.eu/assets/publications/brochures-booklets-and-factsheets/european-steel-in-figures-2022/European-Steel-in-Figures-2022-v2.pdf (visited on 03/03/2023).

European Commission (n.d.). *Allocation to industrial installations*. URL: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/free-allocation/allocation-industrial-installations_en (visited on 05/01/2023).

Farmer, J. D. and D. Foley (2009). "The economy needs agent-based modelling". In: *Nature* 460.7256, pp. 685–686.

Freiberg, D., J. Grewal, and G. Serafeim (2021). "Science-based carbon emissions targets". In: *Available at SSRN 3804530*.

Frimpong, E. T. (2021). *Global Boardroom Diversity: Trends and Updates from the Diligent Institute*. URL: https://www.diligentinstitute.com/commentary/global-boardroom-diversity-trends-and-updates-from-the-diligent-institute/ (visited on 05/02/2023).

Fuchs, D. and J. Clapp (2009). "Corporate power and global agrifood governance: Lessons learned". In: *Corporate power in global agrifood governance*, pp. 285–297.

Galbreath, J. (2010). "Corporate governance practices that address climate change: An exploratory study". In: *Business Strategy and the Environment* 19.5, pp. 335–350.

GID (n.d.). *GISD Iron and Steel Emission Database*. URL: http://gidmodel.org.cn/ (visited on 03/04/2023).

Giesekam, J., J. Norman, A. Garvey, and S. Betts-Davies (2021). "Science-based targets: on target?" In: *Sustainability* 13.4, p. 1657.

Global CCS Institute (2017). *CCS: a necessary technology for decarbonising the steel sector*. URL: https://www.globalccsinstitute.com/news-media/insights/ccs-a-necessary-technology-for-decarbonising-the-steel-sector/ (visited on 08/10/2023).

Government of Canada (n.d.). *Update to the Pan-Canadian Approach to Carbon Pollution Pricing 2023-2030*. URL: https://www.canada.ca/en/environment-climate-change/services/climate-change/pricing-pollution-how-it-will-work/carbon-pollution-pricing-federal-benchmark-information/federal-benchmark-2023-2030.html#toc2 (visited on 05/02/2023).

Greasley, A. (2017). *Simulation modelling for business.* Routledge.

Grimm, V., S. F. Railsback, C. E. Vincenot, U. Berger, C. Gallagher, D. L. DeAngelis, B. Edmonds, J. Ge, J. Giske, J. Groeneveld, et al. (2020). "The ODD protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism". In: *Journal of Artificial Societies and Social Simulation* 23.2.

Grimm, V., E. Revilla, U. Berger, F. Jeltsch, W. M. Mooij, S. F. Railsback, H.-H. Thulke, J. Weiner, T. Wiegand, and D. L. DeAngelis (2005). "Pattern-oriented modeling of agent-based complex systems: lessons from ecology". In: *science* 310.5750, pp. 987–991.

Guest, P. M. (2008). "The determinants of board size and composition: Evidence from the UK". In: *Journal of Corporate Finance* 14.1, pp. 51–72.

Hermwille, L., S. Lechtenböhmer, M. Åhman, H. van Asselt, C. Bataille, S. Kronshage, A. Tönjes, M. Fischedick, S. Oberthür, A. Garg, et al. (2022). "A climate club to decarbonize the global steel industry". In: *Nature Climate Change* 12.6, pp. 494–496.

Hoffmann, C., M. Van Hoey, and B. Zeumer (2020). *Decarbonization Challenge for Steel.* Tech. rep. URL: https://www.mckinsey.com/industries/metals-and-mining/our-insights/decarbonization-challenge-for-steel (visited on 04/13/2023).

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations.* sage.

Höhne, N., M. J. Gidden, M. den Elzen, F. Hans, C. Fyson, A. Geiges, M. L. Jeffery, S. Gonzales-Zuñiga, S. Mooldijk, W. Hare, et al. (2021). "Wave of net zero emission targets opens window to meeting the Paris Agreement". In: *Nature Climate Change* 11.10, pp. 820–822.

ICAP (2023). *Japan's Cabinet approves policy roadmap including plans for national ETS.* URL: https://icapcarbonaction.com/en/news/japans-cabinet-approves-policy-roadmap-including-plans-national-ets (visited on 05/03/2023).

— (n.d.[a]). *China National ETS.* URL: https://icapcarbonaction.com/system/files/ets_pdfs/icap-etsmap-factsheet-55.pdf (visited on 05/02/2023).

— (n.d.[b]). *International Carbon Action Partnership - Mexico.* URL: https://icapcarbonaction.com/en/ets/Mexico (visited on 05/02/2023).

— (n.d.[c]). *Korea Emissions Trading Scheme.* URL: https://icapcarbonaction.com/system/files/ets_pdfs/icap-etsmap-factsheet-47.pdf (visited on 05/03/2023).

— (n.d.[d]). *USA - California Cap-and-Trade Program.* URL: https://icapcarbonaction.com/system/files/ets_pdfs/icap-etsmap-factsheet-45.pdf (visited on 05/02/2023).

ICF (2022). *2021 CHINA CARBON PRICING SURVEY.* Tech. rep. URL: http://www.chinacarbon.info/wp-content/uploads/2022/02/EN_2021-China-Carbon-Pricing-Survey-Report.pdf (visited on 04/29/2023).

IEA (2020). *Iron and Steel Technology Roadmap: Towards more sustainable steelmaking.* Tech. rep. URL: https://iea.blob.core.windows.net/assets/eb0c8ec1-3665-4959-97d0-187ceca189a8/Iron_and_Steel_Technology_Roadmap.pdf (visited on 04/19/2023).

— (2022a). *Achieving Net Zero Heavy Industry Sectors in G7 Members.* Tech. rep. URL: https://www.iea.org/reports/achieving-net-zero-heavy-industry-sectors-in-g7-members (visited on 04/12/2023).

— (2022b). *Global Energy and Climate Model Documentation.* Tech. rep. URL: https://www.iea.org/reports/global-energy-and-climate-model/about-the-global-energy-and-climate-model (visited on 07/03/2023).

IETA (2022). *GHG Market Sentiment Survey 2022.* Tech. rep. URL: https://www.ieta.org/resources/ghg-sentiment-survey/2022-survey/ (visited on 04/27/2023).

IiAS (May 2021). *Indian Board: Structure and Breadth.* Tech. rep. URL: https://www.independentdirectorsdatabank.in/pdf/newsletter/2021/june/Indian_Boards_Structure_and_Breadth.pdf (visited on 04/24/2023).

Insights, H. (n.d.). *Country Comparison Tool.* URL: https://www.hofstede-insights.com/country-comparison-tool (visited on 05/03/2023).

IPCC (2022). “Summary for Policymakers”. In: *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* Ed. by H. O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, and B. Rama. In Press. Cambridge, UK: Cambridge University Press, In Press.

IRENA (2020). *Global Renewables Outlook: Energy transformation 2050.* Tech. rep. URL: https://www.irena.org/publications/2020/Apr/Global-Renewables-Outlook-2020 (visited on 05/01/2023).

Jang, H. and J. Kim (2001). “Korea Country Paper: The Role of Boards and Stakeholders in Corporate Governance”. In: *the Third OECD-Asian Roundtable on Corporate Governance, Singapore*, pp. 1–15.

Ji, J., O. Talavera, and S. Yin (2020). “Frequencies of board meetings on various topics and corporate governance: evidence from China”. In: *Review of Quantitative Finance and Accounting* 54, pp. 69–110.

Jiajun, Z., G. Jing, and T. Hongping (2020). “Data of CEO power, chair-CEO age dissimilarity and pay gap of Chinese listed firms”. In: *Data in Brief* 32, p. 106158.

Khan, A., B. Chan, and K. Downey (2023). *Personal communication.* (Visited on 06/01/2023).

Kiesling, E., M. Günther, C. Stummer, and L. M. Wakolbinger (2012). “Agent-based simulation of innovation diffusion: a review”. In: *Central European Journal of Operations Research* 20, pp. 183–230.

Kizys, R., E. C. Mamatzakis, and P. Tzouvanas (2023). “Does genetic diversity on corporate boards lead to improved environmental performance?” In: *Journal of International Financial Markets, Institutions and Money* 84, p. 101756.

Köhler, J., F. De Haan, G. Holtz, K. Kubeczko, E. A. Moallemi, G. Papachristos, and E. Chappin (2018). “Modelling sustainability transitions: an assessment of approaches and challenges”. In.

Kordsachia, O., M. Focke, and P. Velte (2021). “Do sustainable institutional investors contribute to firms’ environmental performance? Empirical evidence from Europe”. In: *Review of Managerial Science*, pp. 1–28.

Kostyuk, A. (Jan. 2005). “The Kostyuk report: Corporate board practices in Ukraine”. In: *Corporate Board: role, duties and composition* 1, pp. 18–27. DOI: 10.22495/cbv1i1art2.

Kreulen, K., B. d. Bruin, A. Ghorbani, R. Mellema, C. Kammler, L. Vanhee, F. Dignum, and V. Dignum (2022). “How Culture Influences Individual Behavior During a Pandemic: A Social Simulation of the COVID-19 Crisis”. In: *JASSS: Journal of Artificial Societies and Social Simulation* 25.3.

La Porta, R., F. Lopez-de-Silanes, and A. Shleifer (1999). “Corporate ownership around the world”. In: *The journal of finance* 54.2, pp. 471–517.

Lei, T., D. Wang, X. Yu, S. Ma, W. Zhao, C. Cui, J. Meng, S. Tao, and D. Guan (2023). “Global iron and steel plant CO2 emissions and carbon-neutrality pathways”. In: *Nature*, pp. 1–7.

Li, M., T. Wiedmann, and M. Hadjikakou (2019). “Enabling full supply chain corporate responsibility: scope 3 emissions targets for ambitious climate change mitigation”. In: *Environmental science & technology* 54.1, pp. 400–411.

Lister, J. (2018). “The policy role of corporate carbon management: Co-regulating ecological effectiveness”. In: *Global Policy* 9.4, pp. 538–548.

Liu, G. S. and P. Sun (2003). *Identifying Ultimate Controlling Shareholders in Chinese Public Corporations: An Empirical Survey.* Tech. rep. URL: https://www.chathamhouse.org/sites/default/files/public/Research/Asia/stateshareholding.pdf (visited on 05/03/2023).

Lopez, G., J. Farfan, and C. Breyer (2022). “Trends in the global steel industry: Evolutionary projections and defossilisation pathways through power-to-steel”. In: *Journal of Cleaner Production* 375, p. 134182.

LowCarbonPower (n.d.). *Low-Carbon Power: Monitor the Transition to Low Carbon Energy.* URL: https://lowcarbonpower.org/ (visited on 04/04/2023).

Lui, S., T. Kuramochi, S. Smit, M. Roelfsema, A. Hsu, A. Weinfurter, S. Chan, T. Hale, H. Fekete, K. Lütkehermöller, et al. (2021). "Correcting course: the emission reduction potential of international cooperative initiatives". In: *Climate Policy* 21.2, pp. 232–250.

Lyon, T. P. and J. W. Maxwell (2019). ""Voluntary" approaches to environmental regulation". In: *Economic institutions and environmental policy*. Routledge, pp. 75–120.

Macal, C. M. and M. J. North (2005). "Tutorial on agent-based modeling and simulation". In: *Proceedings of the Winter Simulation Conference, 2005.* IEEE, 14–pp.

MarketScreener (n.d.[a]). *ArcelorMittal Income Statement Evolution.* URL: https://www.marketscreener.com/quote/stock/ARCELORMITTAL-34942237/finances/ (visited on 05/05/2023).

— (n.d.[b]). *MarketScreener.* URL: https://www.marketscreener.com/ (visited on 05/10/2023).

Marland, G., T. Kowalczyk, and T. L. Cherry (2015). *Green Fluff"? The Role of Corporate Sustainability Initiatives in Effective Climate Policy: Comment on "Science-Based Carbon Targets for the Corporate World: The Ultimate Sustainability Commitment, or a Costly Distraction?*

Meyer, E. (2014). "Navigating the cultural minefield". In: *Harvard Business Review* 92.5, pp. 119–123.

NewClimate Institute (2022). *2030 Emissions Gap: CAT projections and resulting emissions gap in meeting the 1.5°C Paris Agreement goal.* URL: https://climateactiontracker.org/global/cat-emissions-gaps/ (visited on 01/08/2023).

Nippon (2022). *Average Age of Japanese Company Presidents Reaches 60.3 in 2021.* URL: https://www.nippon.com/en/japan-data/h01278/ (visited on 05/01/2023).

Nippon Steel (n.d.). *Alliances with Steelmakers.* URL: https://www.nipponsteel.com/en/factbook/2022/07-01.html (visited on 04/18/2023).

Nurdiawati, A. and F. Urban (2021). "Towards deep decarbonisation of energy-intensive industries: A review of current status, technologies and policies". In: *Energies* 14.9, p. 2408.

Obayashi, Y. and K. Golubkova (2023). *Explainer: Japan's carbon pricing scheme being launched in April.* URL: https://www.reuters.com/markets/carbon/japans-carbon-pricing-scheme-being-launched-april-2023-03-30/ (visited on 05/03/2023).

OECD (2023). *The Heterogeneity of Steel Decarbonisation Pathways.* Tech. rep. URL: https://doi.org/10.1787/fab00709-en (visited on 04/11/2023).

Ojode, L. (2004). "The impact of horizontal strategic alliances on the US steel industry". In: *Journal of Business Strategies* 21.2, pp. 149–178.

Okereke, C. (2007). "An exploration of motivations, drivers and barriers to carbon management:: The uk ftse 100". In: *European Management Journal* 25.6, pp. 475–486.

Oster, S. (1982). "The diffusion of innovation among steel firms: the basic oxygen furnace". In: *The Bell Journal of Economics*, pp. 45–56.

Poustie, L., C. Vialard, and K. Buchanan (n.d.). *CBAM AND REVISED EU ETS: IMPLICATIONS FOR THE STEEL INDUSTRY.* URL: https://www.shearman.com/perspectives/2021/08/cbam-and-revised-eu-ets-implications-for-the-steel-industry (visited on 04/28/2023).

Ramakgala, C. and G. Danha (2019). "A review of ironmaking by direct reduction processes: quality requirements and sustainability". In: *Procedia Manufacturing* 35, pp. 242–245.

Ramkumar, S., M. Mueller, A. Pyka, and F. Squazzoni (2022). "Diffusion of eco-innovation through inter-firm network targeting: An agent-based model". In: *Journal of Cleaner Production* 335, p. 130298.

Refinitiv (2022). *REFINITIV CARBON MARKET SURVEY 2022.* Tech. rep. Refinitiv Carbon Research. URL: https://www.refinitiv.com/content/dam/marketing/en_us/documents/reports/carbon-market-survey-2022.pdf.

Richardson, K., W. Steffen, W. Lucht, J. Bendtsen, S. E. Cornell, J. F. Donges, M. Drüke, I. Fetzer, G. Bala, W. von Bloh, et al. (2023). "Earth beyond six of nine planetary boundaries". In: *Science Advances* 9.37, eadh2458.

Roelfsema, M., H. L. van Soest, M. Harmsen, D. P. van Vuuren, C. Bertram, M. den Elzen, N. Höhne, G. Iacobuta, V. Krey, E. Kriegler, et al. (2020). "Taking stock of national climate policies to evaluate implementation of the Paris Agreement". In: *Nature communications* 11.1, p. 2096.

Ruigrok, W., S. Peck, and S. Tacheva (2007). "Nationality and gender diversity on Swiss corporate boards". In: *Corporate governance: an international review* 15.4, pp. 546–557.

Sawyer, R. K. (2004). "Social explanation and computational simulation". In: *Philosophical explorations* 7.3, pp. 219–231.

SBTi (2022a). *Science-Based Net-Zero: Scaling Urgent Corporate Climate Action Worldwide.* Tech. rep. URL: https://sciencebasedtargets.org/resources/files/SBTiProgressReport2021.pdf (visited on 02/01/2023).

— (2022b). *STEEL SCIENCE-BASED TARGET SETTING GUIDANCE.* URL: https://sciencebasedtargets.org/resources/files/SBTi-Steel-Guidance-draft.pdf (visited on 04/01/2023).

— (2023). *SBTi CRITERIA AND RECOMMENDATIONS FOR NEAR-TERM TARGETS.* Tech. rep. URL: https://sciencebasedtargets.org/resources/files/SBTi-criteria.pdf (visited on 04/07/2023).

— (n.d.[a]). *SET A TARGET.* URL: https://sciencebasedtargets.org/step-by-step-process#commit (visited on 04/02/2023).

— (n.d.[b]). *Target Dashboard.* URL: https://sciencebasedtargets.org/target-dashboard (visited on 04/09/2023).

Schlüter, M., A. Baeza, G. Dressler, K. Frank, J. Groeneveld, W. Jager, M. A. Janssen, R. R. McAllister, B. Müller, K. Orach, et al. (2017). "A framework for mapping and comparing behavioural theories in models of social-ecological systems". In: *Ecological economics* 131, pp. 21–35.

Schwartz, S. H. (2011). "Values: Cultural and individual." In.

Schwarz, N. and A. Ernst (2009). "Agent-based modeling of the diffusion of environmental innovations—An empirical approach". In: *Technological forecasting and social change* 76.4, pp. 497–511.

Science Based Targets Network (2023). *The first science-based targets for nature.* URL: https://sciencebasedtargetsnetwork.org/how-it-works/the-first-science-based-targets-for-nature/.

Shannon, R. E. (1975). "Systems simulation: the art and science". In: *Prentice-Hall.*

Singal, M. (2014). "The link between firm financial performance and investment in sustainability initiatives". In: *Cornell Hospitality Quarterly* 55.1, pp. 19–30.

SpencerStuart (2022). *Board Governance: International Comparison Chart.* URL: https://www.spencerstuart.com/research-and-insight/international-comparison-chart#metrics (visited on 05/04/2023).

StantonChase (2020). *An Overview of Boards of Directors at Russia's Largest Companies.* URL: https://www.stantonchase.com/wp-content/uploads/2020/09/BoD_Russia_Report_2020_v15_ENG_Final.pdf (visited on 05/02/2023).

Taberna, A., T. Filatova, D. Roy, and B. Noll (2020). "Tracing resilience, social dynamics and behavioral change: a review of agent-based flood risk models". In: *Socio-Environmental Systems Modelling.*

Taras, V., J. Rowney, and P. Steel (2009). "Half a century of measuring culture: Review of approaches, challenges, and limitations based on the analysis of 121 instruments for quantifying culture". In: *Journal of International Management* 15.4, pp. 357–373.

Ten Broeke, G., G. Van Voorn, and A. Ligtenberg (2016). "Which sensitivity analysis method should I use for my agent-based model?" In: *Journal of Artificial Societies and Social Simulation* 19.1, p. 5.

Trexler, M. and A. Schendler (2015). *Science-based carbon targets for the corporate world: The ultimate sustainability commitment, or a costly distraction?*

Van Dam, K. H., I. Nikolic, and Z. Lukszo (2012). *Agent-based modelling of socio-technical systems.* Vol. 9. Springer Science & Business Media.

Van Hilten, E. (2022). *Why corporates join the Science Based Targets initiative: A mixed-method study on the Fortune 500.* Tech. rep. Department of Multi-Actor Systems in the Faculty of Technology, Policy Management at Delft University of Technology.

Vogl, V. and M. Åhman (2019). "What is green steel?: Towards a strategic decision tool for decarbonising EU steel". In: *ESTAD proceedings.* ESTAD 4th, P532.

Vogl, V., M. Åhman, and L. J. Nilsson (2018). "Assessment of hydrogen direct reduction for fossil-free steelmaking". In: *Journal of cleaner production* 203, pp. 736–745.

Waldrop, M. M. (1993). *Complexity: The emerging science at the edge of order and chaos.* Simon and Schuster.

Wang, H. and Y. Jin (2007). "Industrial ownership and environmental performance: evidence from China". In: *Environmental and Resource Economics* 36, pp. 255–273.

Widerberg, O. and P. Pattberg (2015). "International cooperative initiatives in global climate governance: Raising the ambition level or delegitimizing the UNFCCC?" In: *Global Policy* 6.1, pp. 45–56.

Wilensky, U. (1999). *NetLogo (6.2.2.)* URL: http://ccl.northwestern.edu/netlogo/.

Wilensky, U. and W. Rand (2015). *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo.* Mit Press.

Wolf, M. J., J. W. Emerson, D. C. Esty, A. d. Sherbinin, and Z. A. Wendling (2022). *2022 Environmental Performance Index (EPI) results.* Tech. rep. New Haven, CT: Yale Center for Environmental Law & Policy.

World Steel Dynamics (2020). *Strategic Insights: Global Steel Production in 2050.* URL: https://www.steelorbis.com/steel-prices/steel-matters/strategic-insights-cxl-global-steel-production-in-2050no-change-1178634.htm.

Worldbank (n.d.). *Carbon Pricing Dashboard.* URL: https://carbonpricingdashboard.worldbank.org/map_data (visited on 05/10/2023).

WorldSteel (2021a). *Climate change and the production of iron and steel.* Tech. rep. URL: https://worldsteel.org/wp-content/uploads/Climate-change-and-the-production-of-iron-and-steel.pdf (visited on 05/07/2023).

— (2021b). *Scrap use in the steel industry.* Tech. rep. URL: https://worldsteel.org/wp-content/uploads/Fact-sheet-on-scrap_2021.pdf (visited on 04/27/2023).

— (2021c). *Top steel-producing companies: Extended list of companies with tonnage of more than 3 million tonnes (Mt) in 2021.* Tech. rep. URL: https://worldsteel.org/wp-content/uploads/2020_2021-top-steel-producers_tonnage.pdf (visited on 03/20/2023).

— (n.d.). *Total production of crude steel.* URL: https://worldsteel.org/steel-topics/statistics/annual-production-steel-data/?ind=P1_crude_steel_total_pub/CHN/IND (visited on 02/01/2023).

Wunderling, N., R. Winkelmann, J. Rockström, S. Loriani, D. I. Armstrong McKay, P. D. Ritchie, B. Sakschewski, and J. F. Donges (2023). "Global warming overshoots increase risks of climate tipping cascades in a network model". In: *Nature Climate Change* 13.1, pp. 75–82.

Xu, R., D. Tong, S. J. Davis, X. Qin, J. Cheng, Q. Shi, Y. Liu, C. Chen, L. Yan, X. Yan, et al. (2023). "Plant-by-plant decarbonization strategies for the global steel industry". In: *Nature Climate Change*, pp. 1–8.

Zaid, M. A., M. Wang, M. Adib, A. Sahyouni, and S. T. Abuhijleh (2020). "Boardroom nationality and gender diversity: Implications for corporate sustainability performance". In: *Journal of Cleaner Production* 251, p. 119652.

Zhang, D., Z. Zhang, Q. Ji, B. Lucey, and J. Liu (2021). "Board characteristics, external governance and the use of renewable energy: International evidence". In: *Journal of International Financial Markets, Institutions and Money* 72, p. 101317.

Appendix A

ODD model description

This appendix described the developed agent-based model using the logic of the ODD protocol from Grimm et al. (2020). For many aspects of the model, this appendix will provide more detail and in doing so sometimes overlap with the main text. For other parts, the main body of text is referred to as a detailed and comprehensive explanation of that particular topic is also included there.

A.1 Model purpose

When models concern the simulation of socio-technical systems, they often fall in one of the seven purpose categories outlined by Edmonds (2017). This study, and therefore the developed model, aims to bring a more in-depth understanding of what motivates companies to take climate action - and more specifically, steel companies to commit to science-based decarbonisation targets. As such, the developed model falls in the category of 'explanation'. More concretely, the model is used to analyse a number of scenarios and compare their results. Instead of focusing on absolute outputs, such as the exact number of committed companies by 2050 in a certain scenario, this study thus focuses on comparative metrics. As in explanatory models there is room to study a possible causal relationship, this type of simulations allows to test the effects of changes in certain independent variables.

The model is therefore developed to understand the drivers behind corporate climate action, specifically focusing on a number of independent variables that are altered in the different scenarios. In doing so, it is the aim that stakeholders and cooperative initiatives such as the SBTi can find value in the results and use the findings to steer more companies towards climate action.

A.2 Entities in the model, their attributes and their temporal and spatial limits

Entities

Following the scope of this study, the model only considers steel companies as agents. Specifically the studied population of companies includes two groups, (i) the 113 largest steel producers globally in 2021 (production > 3Mt) and (ii) the present members of WorldSteel that do not fall in the first category. Note, however, that companies which fall within one of the above mentioned groups but have headquarters outside of the geographical scope of this study were excluded. As will be elaborated on under 'Scales' certain companies were then split, resulting in a final population of 163 steelmakers. In the model, the companies are part of global alliances following the random creation of linkages and consider other, similar-sized, steelmakers on their continent as competitors.

Additionally, the environment is an important entity in the model. Through environmental phenomena such as carbon pricing and the availability of technological factors, agents' decision-making is influenced. Moreover, the impact of stakeholder pressure is a noteworthy environmental variable that is represented in the model. Acknowledging that stakeholder dynamics are complex, the perception of stakeholder pressure by the agents is only modelled as a simplified variable in line with the study's scope.

Attributes

Figure D.2 and Figure D.1 outline the model variables and parameters that directly or indirectly influence agents' decision-making. Though all are important in the model, the most crucial state variable is *Commitment_status*. A value of 0 for this variable signals that a company has not yet adopted science-based emission reduction targets. If a company has a value of 1 for this variable, it entails that the company has adopted SBTs. Following this, it will no longer perform the decision-making process regarding SBT adoption. Moreover, measuring how many companies in the end adopt is useful to answer sub-question III.

Scales

Regarding the temporal dimension, the starting point of the model is 2023, as was elaborated on in Section 1.3. The model is run for a period of 13 years, until the end of 2035. This time frame seems appropriate in simulating the dynamics between companies in their SBT related decision-making processes and the increasing uncertainty that longer time horizons would result in (Taberna et al., 2020).

Table A.1: Time between decision moments for companies in each respective country.

Country	Meetings/year	Decision every	Source
China	10.7	2 ticks	Ji et al. (2020)
Japan	14	2 ticks	SpencerStuart (2022)
India	7.5	3 ticks	SpencerStuart (2022)
South Korea	22	1 tick	Jang et al. (2001)
Germany	8*	3 ticks	SpencerStuart (2022)
Italy	13	2 ticks	SpencerStuart (2022)
Spain	13	2 ticks	SpencerStuart (2022)
Russia	6.8	4 ticks	SpencerStuart (2022)
Turkey	27	1 tick	SpencerStuart (2022)
Ukraine	5.4	4 ticks	Kostyuk (2005)
USA	9	3 ticks	SpencerStuart (2022)
Canada	10	2 ticks	SpencerStuart (2022)
Mexico	4.2	6 ticks	SpencerStuart (2022)

Note that the number of weeks between decision moments was calculated using a 48-week year. This value was then divided by two (one tick = two weeks) and rounded to the nearest integer.

** The value used for board meeting frequency in Germany was based on the average number of board meetings held by German steel producer Thyssenkrupp.*

From the start of 2023 until the end of 2035, the model runs using time steps (i.e. ticks) that each represent two weeks. Moreover, a year in the model is assumed to consist of 12 months with 4 weeks each (i.e. 48 weeks). As Arvitrida et al. (2017) argue, when modelling company decision-making behaviour, the chosen time unit should adequately represent the time needed for an organisation to alter its strategy. As such, it was determined that companies have the possibility to commit to SBTs at every board meeting. The average number of board meetings per country is used as an indicator of how many board meetings a company in a specific country has (Table A.1).

Concerning the spatial dimension, the exact location of companies on the modelled grid is not important. Rather, the location of companies is incorporated through three parameters: *country*, *region* and *continent*. For most variables, the country of operation is the important geographical determinant for data distribution. For example, the Hofstede dimensions included in the study have country level scores that (using an assumed normal distribution, see Appendix A.5) are allocated to each company in the respective country. Nonetheless, some data was not available on the country level, due to which regional estimates were used. Lastly, the continent of each company is relevant as companies are assumed to compete only with other steelmakers - of a similar size - on the same continent.

Moreover, as has been explained in Section 1.3, this study uses a number of proxy countries to represent the regions. As data was only collected for these countries, it was necessary to assign a proxy country to all included companies that were not from one of the proxy countries. For example, Luxembourg is part of Europe and thus included in this study, but no data was collected for Luxembourg specifically. Instead, companies headquartered in Luxembourg were assigned to one of the EU proxy countries using production output based probabilities[1]. Additionally, the largest firms (>12Mt annual production in 2021) were split into multiple (regional) companies based on regional sales revenues[2] if their main market made up less than 60% of total revenues. These split companies were assigned a proxy country in the relevant region in the same way as was described above. For all state-owned companies and all steelmakers with total production below 12Mt, it was assumed that their full operations and production take place in the country of their headquarters. For an overview of the included companies and assigned proxy countries, please refer to Appendix E.

A.3 Outline of the processes and model scheduling

Figure 5.3 (main text) gives an overview of the decision-making process of an agent in the model. Though computer models can only run simulations subsequently, the figure and description below assume that all steelmakers make decisions in parallel (every time step).

Before starting the agent decision-making process, the model setup is initialised and every steelmaker determines if there is a board meeting this specific time step. If that is not the case, the agent will not go through the SBT decision-making process. However, if the steel company does have a board meeting, there exists a moment to assess the possibility of adopting SBTs.

In this case, it is first important that the board establishes if the firm has already committed to SBTs or not. If the company is already committed, there is no need to have an extensive decision-making process. The corporate boards of uncommitted steelmakers, however, determine what their attitude is towards the behaviour of committing to SBTs. Moreover, they assess to what extent there is social pressure to engage in SBT adoption (i.e. the subjective norm). The determination of these two constructs follows the reasoning of the Theory of Planned Behaviour and is done using the mathematical logic outlined by Azjen (2019). This is in detail covered in Section 5.1.

[1]For example for the countries in the EU, the probabilities were calculated as follows: Germany has a production output of 40.1Mt, Italy of 24.4Mt, and Spain of 14.2Mt. The total production of these countries is 78.7Mt. Companies from other EU countries thus have a 51% (40.1/78.7) chance of being assigned Germany as proxy, a 31% chance of being assigned Italy and an 18% chance of being assigned Spain

[2]For example, if a company generates 40% of revenues in the EU, 30% in non-EU and 30% in China, the company was split into three companies (e.g. ArcelorMittal – EU, ArcelorMittal – Non-EU and ArcelorMittal – China) with production volumes being split based on the regional sales revenues.

If a steel company has a combination of a very strong positive attitude or subjective norm towards SBT adoption, with a reasonably strong positive feeling for the other, it will decide if it has the behavioural control to successfully take climate action. Though according to Bosnjak et al. (2020) there exists a difference between the perceived and actual behavioural control of an actor, the authors also argue that the former can be used as a proxy for the latter. As such, perceived and actual behavioural control are modelled as one and the same construct, considering that there is no data available to make a distinction.

With enough (perceived) behavioural control, a company decides to commit to SBT setting. Normally, the control of a company moderates its relation between intent and action (Bosnjak et al., 2020), however, this is incorporated in the modelling by using a threshold. If the behavioural control exceeds that threshold, it is assumed that the moderation of the relation is strong enough for an agent to take action based on its intent.

At last it is determined if the simulation has already finished (end of 2035) in which case the simulation is stopped. If the simulation has not yet reached its end, the number of ticks is increased by one and all variables for which the number of ticks matter are adapted. The process then starts from the beginning again, now taking into account the new variable values.

A.4 Design concepts of the ABM

Basic principles

Agents (i.e. companies) in the model make decisions following the Theory of Planned Behaviour. The model consists of a heterogeneous population of agents, who are influenced by their own characteristics, the behaviour of other agents and environmental factors in their decision to adopt (or not adopt) science-based emission reduction targets.

Emergence

As the agents make decisions in the model, they influence other agents. Specifically, by committing to SBTs, an agent gives a signal to its allies and competitors that the status quo is changing. The allies and competitors will use this information in their decision to adopt SBTs at their next decision moment. Emergence in the modelled system may thus refer to the overall behaviour of the system that will emerge from the commitment decisions of individual but interacting companies.

Adaptation

There are two phenomena that cause steelmakers in the model to show adaptive behaviour.
Firstly, certain traits that characterise agents (e.g. board diversity) or the environment (e.g. low-carbon electricity availability) are coded into the model to change over time. The companies will respond to these changes and adapt their attitude and perceived behavioural control accordingly.

Secondly, as has been specified and will be elaborated on later, the agents in the model base their decisions on the outcomes of the previous decisions from competitors and allies. As such, depending on what the connected companies in the model did in the previous time step, agents will make a certain decision in the current time step.

Objectives

Within the model, agents want to maintain a competitive position with respect to their competitors, while they simultaneously have some drive to take climate action (i.e. adopt SBTs). The extent to which agents value their financial and environmental performance depends on their characteristics. For steel companies there exists a risk that their financial performance will decrease if it increases its environmental performance. Only under certain circumstances will a company thus be willing to take some financial risk in order to take climate action. The objective of the model is therefore to simulate this low-level behaviour among companies and keep track of how many agents in certain scenarios actually commit to SBTs.

Learning

There is no learning incorporated in the model in the sense that 'learning' entails changing the equations that govern agent-level decision-making. However, the adoption behaviour of the other companies will result in a new value for (in this case) *Competitor_commitment*. In a way, the company learns about the actions of other steelmakers, and uses this to make its own decision.

Prediction

Prediction is relevant to the model in two ways. Agents themselves make some sort of prediction on how adopting SBTs will affect them. The modelled companies make an assessment of the forces driving climate action and those inhibiting it. A company will then act when it predicts that it is more beneficial to commit to setting SBTs than it is to stay uncommitted.

Additionally, the model is run over a time period of 13 years. A number of the agent-level and environmental characteristics therefore evolve over time based on predictions. For example, the actual carbon price in the EU by 2030 is unknown, but expert estimates are used to model a dynamic price level. Such predictions come with substantial uncertainty[3] and are inherently biased by the experts who made them.

Sensing

Apart from the between-agent interactions and agent-environment interactions that have been described and will be further elaborated on below, it is important to mention the networks in which agents interact here. Specifically, agents are modelled into a network that represents global alliances between companies. This is done by giving each company the task to link itself with a number of other steelmakers (*Create_links* represents that number). With which other companies a specific firm decides to link itself is a random process. Additionally, agents exist in a competitor network based on their continent of location and size. Companies in the model are assumed to know the information relevant to them (e.g. access to low-carbon electricity), thus no process is modelled in which steelmakers seek for or try to obtain this information.

Interaction

As was established in the beginning of this section, the entities interacting in the model are agents – as steelmakers, competitors and allies – and the environment. Concretely, the modelled steel companies therefore interact with their competitors, their allies and the environment.

Interaction between a steel company and its competitors

Every steelmaker operates in one of the three covered continents (i.e. North America, Europe and Asia). Based on the continent of location and a company's *Size_classification*, steel companies compete with each other. At the moment a company commits to science-based targets, it sends a signal to the other steelmakers on the same continent that commitment is becoming more common in the sector. Through such interactions, companies exert pressure on each other.

Interaction between a steel company and its allies

Similar to the interaction between a steelmaker and its competitors, steel companies care about the activities of their allies. As has been mentioned, in the model agents are linked randomly with a number (two by default) of other firms. When a company in such an alliance commits to SBTs, it notifies the

[3]In the case of the EU emissions trading systems (ETS), the estimated future price levels are based on an expert survey conducted by (IETA, 2022). In the report outlining the findings, the authors show that predictions made just one year before were already not accurate anymore.

other alliance members that setting SBTs is becoming more widespread. The inclusion of alliances in the modelled system thus allows to incorporate behavioural spillover effects in the study.

Still, the extent to which a steelmaker considers its allies' SBT-related actions as relevant, is dependent on the level of individualism of that company. Individualism is one of Hofstede's (2001) cultural dimensions. Since decisions in companies (such as steelmakers) are made by people, it is assumed that Hofstede's cultural dimensions are also applicable to agents in this study. Individualism encompasses the degree of loyalty and interdependence between members of an 'in group', which in this case is assumed to be the alliance. In the case that a company scores high on this dimension, it is 'individualistic' and will value less what its allies are doing regarding SBT adoption. If a company has a high score, however, it is 'collectivistic' and will be more strongly motivated to mimic the other members in its alliance.

Interaction between a steel company and its environment

Apart from interacting with other agents, the behaviour of modelled steel companies is determined by some financial and technological environmental factors.

Through the pricing of carbon, steelmakers are incentivised to reduce their GHG emissions and potentially commit to SBTs. Of the proxy countries studied in this project, only China, South Korea, Canada and the EU countries have a carbon price that covers the steel industry. All these countries excluding Canada utilise an emissions-trading-scheme (ETS), while Canada uses a carbon tax. Considering that not all covered countries currently have a carbon price on steel, a *Price_pressure* of zero was assumed for the companies in countries where emitting GHGs is free. It should be acknowledged that some countries with currently no carbon price have plans for establishing an ETS or tax, but due to the great uncertainty of timescales, coverage and future price levels such potential plans were excluded from analysis (for elaboration, see Appendix A.5).

Additionally, it is noteworthy that at present a lot of emission rights are allocated for free to companies in the steel sector. This is incorporated in the model by making a distinction between the market carbon price (*Carbon_price*) and the perceived carbon price (*Perceived_price*) by incorporating the share of free allowances (*Free_allowances*). Moreover, in order to standardise the pressure from carbon pricing, it was assumed that a value equal to or over 95 (€) for *Perceived_price* corresponds to maximum pressure. The €95 threshold was taken from Hoffmann et al. (2020), who argue that a carbon price between €55 and €95 is enough to make green hydrogen less costly than grey hydrogen (depending on the electricity price). As the authors base their estimate on Germany, however, the most conservative estimate was taken to determine what value for *Perceived_price* should constitute the max value for *Price_pressure*.

Another influential environment-dependent factor is the availability of steel scrap for production. However, although steel scrap can be recycled, it is not only the amount available that should be considered. Rather, as steel production is also estimated to increase over the course of the model, the intensity (i.e. share of scrap in total production) is assessed. Note, however, that exports and imports are ignored (as was explained in Section 1.3). The progress of scrap intensity over time is assumed to be linear and is discussed more in Appendix A.5.

Finally, as was established in Section 3.3, it is worthwhile to consider the proportion of economic activities that could be conducted using low-carbon electricity. Therefore, it has been analysed what part of country-level electricity generation is done using renewables and is expected to be achieved in the future (again, see Appendix A.5).

Stochasticity

Through stochasticity, models can incorporate some of the uncertainty that is inherent to the real-world system it aims to represent. In the model used in this study, the concept is applied as follows:

At the initialisation of the model setup, many of the characteristics of agents are determined using normal distributions. Simultaneously, the form of ownership of each steelmaker is based on a probability that represents the real world (Appendix A.5). Moreover, there is some randomness in the assigning of companies to their allies. As the setup of the randomly linked network may influence the model's results, companies are re-matched every simulation run.

Collectives

Modelled collectives in which the agents take part include its competitors and its alliance, which are both explicitly modelled and were in more detail explained above.

Observation

The main aspects that are tracked in each simulation are the number of committing companies, the amount of companies that develop intention and some of the characteristics of the companies that are committing. Using this, the aim is to observe patterns in the data in order to formulate an adequate answer to the research question.

A.5 Initialisation and input data

This section outlines the data used for the initialisation and simulation of the ABM. By sharing where the data was obtained and what exact values are used, it is the aim to improve the transparency and reproducibility of this study for future research and scrutiny.

Carbon pricing

The Worldbank (n.d.) keeps track of the developments around carbon pricing on their 'Carbon Pricing Dashboard'. Using this tool, grey and white literature and other web-based resources, the carbon prices per region were determined. The exact starting values and computed linear slopes are outlined here, but the equations with which *Price_pressure* is determined are given in Section 5.1.

In the EU

The countries that constitute the EU-28 have a carbon price that is determined by the EU emissions trading scheme (EU-ETS). Though the steel sector is included in the EU-ETS, is has in the past and present always been granted free allowances because the sector is believed to be at high risk for carbon leakage. Since the EU is implementing its CBAM in the coming years, the number of free allowances for companies in sectors with a high risk of leaving will be reduced accordingly.

Concretely, the EU had a carbon price of €83.30 on the first of January 2023. The number of free allowances for the steel sector at that time still covered 100% of its emissions (European Commission, n.d.). From 2026 onwards, the number of free allowances will be reduced by 10% each year compared to 2025 (i.e. by 10%-point each year). In 2035, the number of free allowances will thus be zero (Poustie et al., n.d.). Though in real life the free allowances are not distributed equally to all steel-making companies, in the model it is assumed they are. In other words, the assumption is made that every steelmaker receives the same relative share of free allowances per year.

Furthermore, experts expect that the EU carbon price will be higher than 100€/ton of emitted GHG emissions by 2030 (Refinitiv, 2022). Another panel of experts suggest that the carbon price under the EU-ETS will be an average of €99.63 between 2026 and 2030 (IETA, 2022). As such, it is assumed that the (average) price for GHG emissions in the EU will be €99.63 in 2028. The calculated slope by which the carbon price then increases every time step (two weeks) - assuming linearity - is 0.136€. For the equations used to determine the *Price_pressure*, please refer to Section 5.1.

There also exist a number of country specific emission trading systems and carbon taxes within the EU, however these are complementary to the EU ETS. As such, they are excluded from analysis.

In the Non-EU

The three proxy countries in Non-EU currently do not have an ETS or carbon tax. Turkey has plans for an ETS system, but the country is first going to run some pilots. Ukraine was planning on setting up an ETS, however, these plans have been interrupted by the invasion of the country by Russia. The latter has no mentioned plans for a carbon price (Worldbank, n.d.).

As the scope, time frame and price levels of a proposed carbon price in any of the Non-EU proxy countries is highly uncertain, the assumption is made that there will be no carbon pricing in this region until at least 2036.

In the United States

Though certain states have their own carbon pricing regulations, the main carbon markets in North America are the Regional Greenhouse Gas Initiative (RGGI) and the Western Climate Initiative (WCI). Of these, only the latter puts a price on the emissions coming from the production of steel (ICAP, n.d.[d]). However, there is merely one US state connected to the WCI, which is California. Since the emissions from the steel sector in California are less than 0.8% of the state's total emissions (Figure A.1), it is assumed that the carbon pricing of steel production in this state is negligible. Moreover, there is no evidence that the RGGI will include steel sector emissions in the coming years and experts do not believe there will be a federal US carbon price soon (IETA, 2022). As such, no carbon price is modelled for the US.

In Other-NA

In the region of Other-NA, the two proxy countries are Mexico and Canada. The former of these is working on the implementation of an ETS that was expected to be operational from 2023 onwards (IETA, 2022). However, the current development status and actual/future carbon price remain unclear (ICAP, n.d.[b]). On the other hand, Canada has implemented a (minimum) carbon tax for steel-based emissions. That is, Canadian provinces often have their own carbon pricing mechanisms (e.g. some states are part of the WCI) but the nationwide tax is set as a lower bound (Government of Canada, n.d.). The carbon tax started in 2023 at $65CAD and is set to increase by $15CAD until it reaches $170CAD by 2030. Since it is a tax and not an ETS, there are no free allowances allocated to the different steelmakers in Canada. Thus, it is assumed that no companies are exempt from paying the carbon tax.

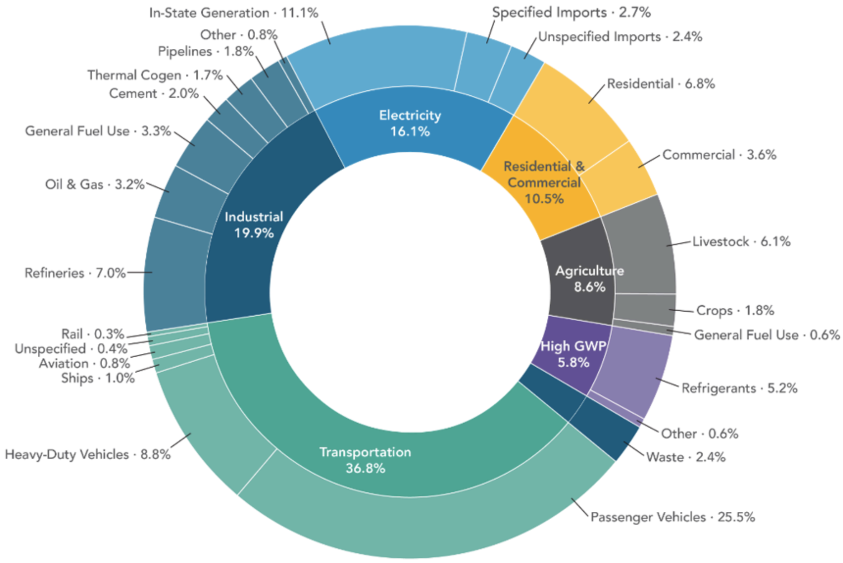


Figure A.1: Inventory of proportional GHG emissions per sector for California (Source: California ARB (2020)).

Altogether, the model will not include a carbon price for Mexico due to the large uncertainties with the country's ETS. The price (€) for Canada will be modelled using an estimated (linear) slope of 0.415€ and a starting value of €43.13[4].

In China

In recent years, China has been piloting an ETS program for the energy industry. This was extended to a national emission-intensity based trading system in 2021, which by size of emissions covered is the largest in the world (ICAP, n.d.[a]). Nonetheless, emission allowances are at the moment freely distributed. Auctioning will become the norm in the future, but the timeline for this is uncertain (ICAP, n.d.[a]). As the ETS is focused on the energy generation sector, steel manufacturing is not included. However, two expert surveys conducted by (Refinitiv, 2022) and (ICF, 2022) estimate that the steel sector has a very high probability of being included before 2025. With the Refinitiv survey actually concluding that steel is the most likely to be added sector in the near term. Similarly to the EU, the expert estimation by the IETA (2022) panel is used as an estimate for the future pricing of GHG emissions in China. Concretely, the projection made argues that the average carbon price between 2026-2030 will be €44.82. This value is assumed the average carbon price in 2028, so that a linear relationship can be extrapolated from the pricing data. As there exists large uncertainties regarding the auctioning timeline

[4]Please note that the actual carbon price is in CAD, but for consistency in the model the amount of CAD has been translated into a euro value. This is done for all prices that were not given in euros.

of allowances in the country's ETS, it has also been assumed that all allowances are provided for free up to the end of 2030. After 2030 (i.e. from 2031 onwards), the number of free allowances will decrease by 10% compared to 2030 at the beginning of each year. In 2036, the share of free allowances will thus be 40%. To model the Chinese carbon price, a slope of 0.313€ and starting value for *Carbon_price* of €7.32 are used.

In Other Asia

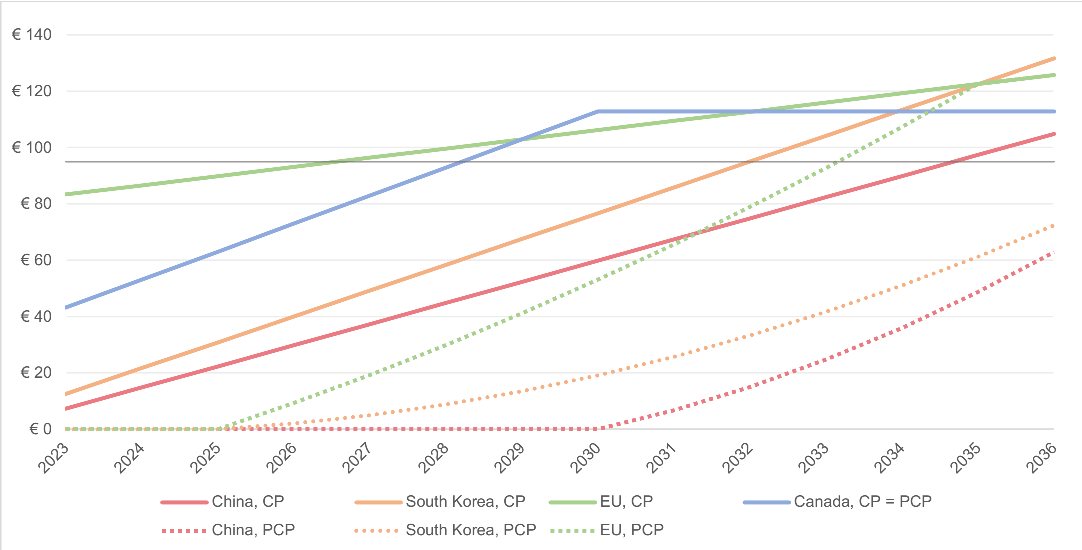
Concerning the proxy countries in Asia outside of China, only South Korea has an ETS that is presently in force. The ETS covers the steel industry, but it is not completely clear what share of the emission allowances are distributed for free to the sector. Normal sectors receive approximately 90% for free until 2025, however, industries with a high risk of carbon leakage get 100% of allowances without paying (ICAP, n.d.[c]). As the steel sector is generally considered of high risk regarding carbon leakage, it is assumed steelmakers in South Korea receive 100% of allowances for free until the end of 2025. Afterwards, steelmakers are treated as normal companies (free allowances = 90%). Moreover, as the South Korean government is expected to raise the share of allowances that are auctioned out in the near future (ICAP, n.d.[c]), the assumption is made that the share of free allowances will decrease by 5%-point annually from the beginning of 2027 onwards. The value for *Carbon_price* for South Korean companies at the start of the model will be €12.51 and this value will increase with €0.382 every step.

Apart from South Korea, the other two major steel producing countries in the region do not have an established carbon market. Data from the World Bank indicates that a tax or ETS system is currently not under formal consideration in India (Worldbank, n.d.). In Japan, however, it will become mandatory for steel producers to take part in the national ETS system from April 2026 onwards (Obayashi et al., 2023). Nonetheless, allowances are set to be auctioned only after 2033 and price levels for the period after have not been determined (ICAP, 2023). Taking all this information into account, the assumption is made that modelled steelmakers in Japan and India do not incur a price on the GHGs they emit over the time horizon of the simulation.

Summary on modelled carbon pricing

Only for China, the EU countries, South Korea and Canada a carbon price is modelled. The projected price behaviour is linear based on past data. Moreover, since future price estimates are higher than current carbon prices, carbon prices will go up in all countries as the model furthers in time (Figure A.2). It should be acknowledged that there are strong uncertainties surrounding future price estimates, especially for the countries that utilise an ETS. However, carbon pricing is modelled to the best of the ability of the researcher, considering time and data constraints.

Figure A.2: Projected carbon price (CP) and perceived carbon price (PCP) per relevant area (Source: Author).



Note: The carbon price and perceived carbon price are the same for Canada, as it is believed that this country offers no free allowances to the steel industry. The 95€ barrier represents the (perceived) carbon price-level from where onwards the pressure from carbon pricing results in a score of 100 (i.e. maximum) for Price_pressure.

Board diversity, size and age

Since the board of directors is the most important decision-making organ in most corporations, its characteristics define to what extent a company holds a positive attitude towards something. Specifically, in order to establish heterogeneity among the modelled steelmakers, it has been important to find data on the share of women in the board across nations, the average age of directors and the average size of boards.

Board diversity

In order to proxy the diversity among board members, data was obtained on the share of directors that is female. This data came predominantly from Deloitte's 4th, 5th, 6th and 7th edition of its 'Women in the Boardroom' reports (Deloitte, 2015; Deloitte, 2017; Deloitte, 2019; Deloitte, 2021). Earlier editions did not list data for most studied countries and were therefore omitted from analysis. Table A.2 outlines the data used to compute a trend. The data used is not specific for the steel industry but was assumed to be representative.

Table A.2: Average share of women on corporate boards (%)

Note: (e) = estimated

Country	**2014**	**2016**	**2018**	**2021**	**2023 (e)**
Russia	5.7	5.8	8.5	10	11.6
Ukraine	NA	NA	NA	18.3	20.5
Turkey	10	11.5	13.2	15.1	16.7
India	7.7	12.4	13.8	17.1	19.9
Japan	2.4	4.1	5.2	8.2	9.6
South Korea	1.7	2.5	2.4	4.3	4.6
China	8.5	10.7	10.6	12.6	13.5
US	12.3	14.2	17.6	23.9	26.6
Canada	13.1	17.7	21.4	27.8	31.9
Mexico	6.2	6.0	6.5	9.7	9.9
Germany	18.3	19.5	26.2	28.9	33.3
Spain	12.5	16.3	19.2	26.3	29.6
Italy	22.3	28.1	29.3	36.6	39.8

To reflect the heterogeneity between agents and the effect of firm size (which is positive for board diversity, see Section 3.3), initial values for *Share_female* were assigned to steelmakers using a normal distribution. The normal distribution is region-based, meaning that all steelmakers in a certain region (e.g. Other Asia or United States) get a value from the normal distribution that represents their specific region. Though country specific values for *Share_female* are available, the normal distribution is based on the region so that a standard deviation can be calculated.

The mean for each region was determined by taking the average of the highest and lowest country-level value for the proportion of women for that specific region. For example, for Non-EU the highest value in 2023 is 20.5% (Ukraine) and the lowest Russia (11.6%). The average for the region is thus calculated with these two values, while not taking into account the proportion of women on boards in Turkey. This may make the estimated mean for the region a little less accurate, but allows to make an important assumption in the calculation for the standard deviation. In essence, for Non-EU this method results in a mean of: (20.5+11.6)/2 = 16.05%. However, as firm size (positively) influences the diversity among board members, this effect also has to be incorporated. Therefore, if a firm is classified as 'Large' the calculated regional mean is increased by 30% (through *Size_effect_diversity*) to get the actual mean that will be used in the initial distribution of scores for *Share_female*[5]. Similarly, if a company is 'Small', a 30% lower mean is used and if it is 'Medium' the regional mean is used in the allocation (Figure A.4).

The regional standard deviation is then computed by assuming that both the highest and lowest country-

[5]In the case of large companies in Non-EU, the mean used will thus be: 16.05 * 1.3 = 20.87

level values (i.e. those values that were used to compute the regional mean) are two standard deviations away from the mean. In the case of Non-EU, the standard deviation will thus become: (20.5 – 16.05) / 2 = 2.22. However, this is only possible for regions with multiple proxy countries and therefore not for the United States and China. Instead, the standard deviation for these regions was assumed to be the same as for the other region on their respective continents (i.e. Other-NA and Other Asia) but scaled up or down to account for a higher or lower regional mean. Regarding the United States, for instance, the standard deviation was determined by multiplying the standard deviation of Other-NA with Mean_{USA} / $\text{Mean}_{\text{OTHER-NA}}$. The normal distributions per region are shown in Figure A.3.

Figure A.3: Normal distributions of the share of women on corporate boards, per country (Source: Author).

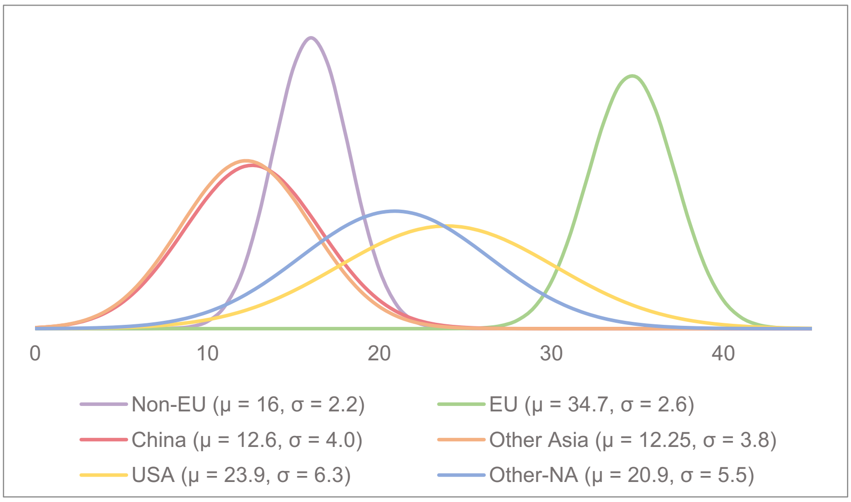
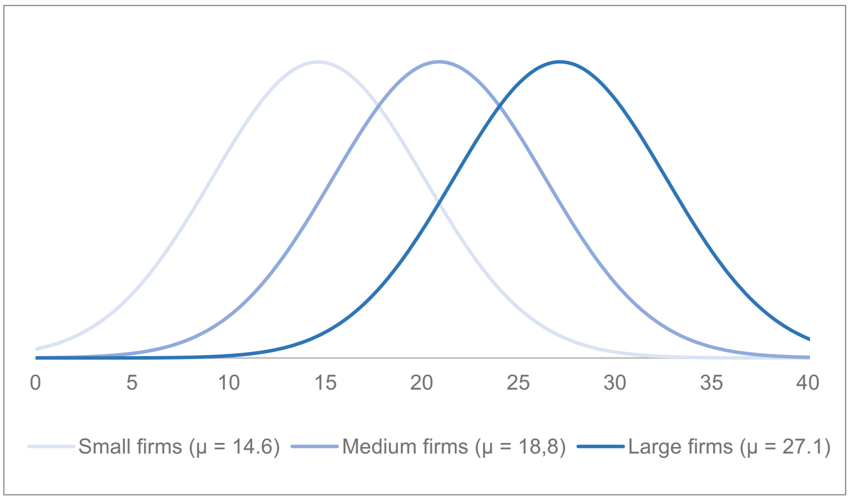
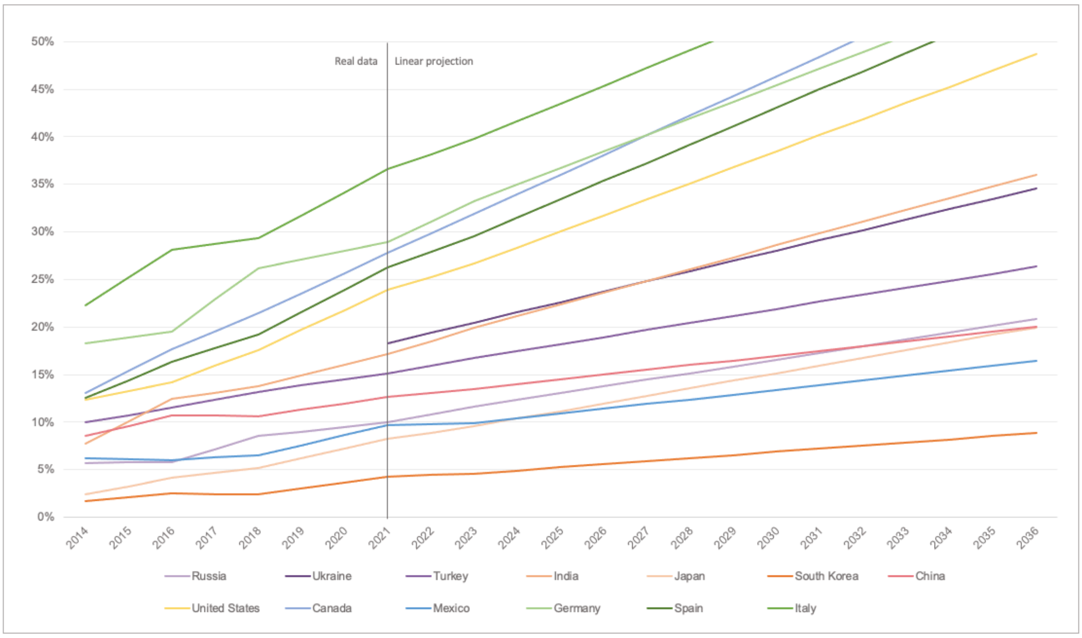


Figure A.4: Visualisation of the effect of firm size on the share of women in a company's board (Source: Author).



With the initial values for *Share_female* established, it is also important to incorporate how board diversity may change over time (*Share_female_slope*). As such, the Excel TREND function was used to estimate future diversity levels based on past data (Figure A.5). In doing so, it is assumed that the share of women will not go over 50%, as this proportion of women on the board results in the highest score for *Board_diversity*. Moreover, as Ukraine data for 2014, 2016 and 2018 is not available, a simple average of the slope of Russia and Turkey (the other two countries in Non-EU) was taken as the slope for Ukraine's change in diversity. Moreover, as with many of the modelled variables, board diversity is assumed to change every two weeks as this is one time step in the model. In reality, new board members may be appointed fewer times a year and the change in diversity is more discreet.

Figure A.5: Estimated increase in the share of women on corporate boards, per country (Source: Author).



Altogether, the initial values for *Share_female* per company will thus come from an allocation with a normal distribution based on the explained calculations above. This proxy for board diversity will then change over time depending on the trend found in past data. Finally, *Board_diversity* is determined following Equation (5.7) outlined in Section 5.1.

Board size

Concerning the number of members on a company's board, average values were obtained on a country level (Table A.3). To distribute values for the size of a board to the particular companies, a normal distribution with a standard deviation of 1.5 was then assumed. More concretely, modelled steelmakers in for example China thus receive a value for the number of board members from a normal distribution with a mean of 6 and standard deviation of 1.5.

However, since company size is a determinant of the number of board members, this effect has to be incorporated in the study. Therefore, similar to the approach taken to allocate values for *Board_diversity*, firms with a size classification of 'Medium' used the value given in Table A.3 as the mean for the normal distribution. 'Large' or 'Small' companies, however, were allocated with a 30% higher or lower mean, respectively (through *Size_effect_board*). The used standard deviation is the same for all firms.

Lastly, it is important to note that a value of one was set as the lower limit for *Board_size*, as a lower value would entail that the respective company has no board.

Table A.3: Overview of the average number of directors in a corporate board across countries

Country	Average number of board members	Source
Russia	11	StantonChase (2020)
Ukraine	9	Kostyuk (2005)
Turkey	9.5	SpencerStuart (2022)
India	9.1	IiAS (2021)
Japan	11	SpencerStuart (2022)
South Korea	10.1*	NA
China	6	T. Chen (2015)
USA	10.8	SpencerStuart (2022)
Canada	11	SpencerStuart (2022)
Mexico	11.6	SpencerStuart (2022)
Germany	5	SpencerStuart (2022)
Spain	11	SpencerStuart (2022)
Italy	11	SpencerStuart (2022)

Note: As no value for South Korea was found, the average number of board members for the country is represented by a simple average of India and Japan.

Board age

The last important characteristic of the corporate board is the average director age. Table A.4 provides the average board age for the studied countries. Again, the allocation of average board ages to different companies was done by assuming a normal distribution. However, in order to determine the relevant standard deviation, the ages were averaged on a regional level. The regional average and standard deviation were thus used to distribute board age values to the various steel companies. The differences between the regional normal distributions are visualised in Figure A.6.

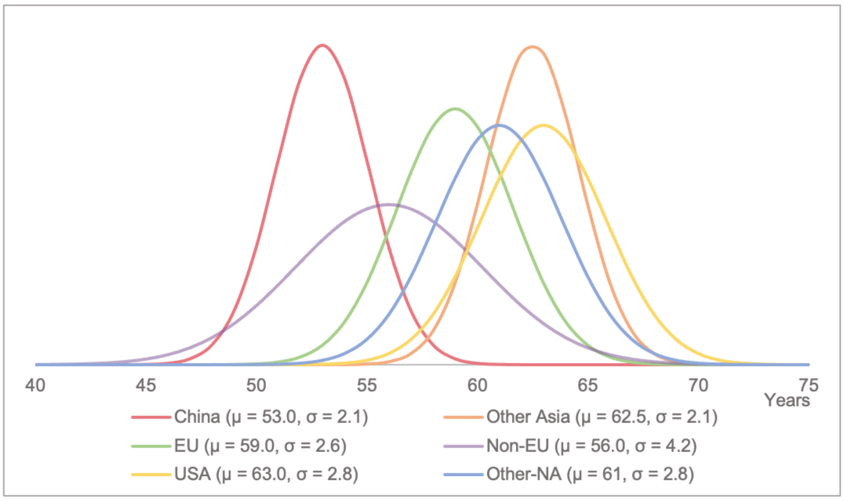
Table A.4: The average and standard deviation of board ages in the studied regions

Country	Country average	Region	Region average	Standard deviation	Source
China	53	China	53	2.12**	Jiajun et al. (2020)
Japan	61	Other Asia	62.5		Nippon (2022)
India	64				IiAS (2021)
South Korea	62.5*				NA
Germany	57	EU	59	2.65	Frimpong (2021)
Italy	58				Frimpong (2021)
Spain	62				Frimpong (2021)
Russia	53	Non-EU	56	4.24	StantonChase (2020)
Turkey	59				SpencerStuart (2022)
Ukraine	56*				NA
USA	63	United States	63	2.83**	Frimpong (2021)
Canada	63	Other-NA	61		Frimpong (2021)
Mexico	59				SpencerStuart (2022)

**Simple average of other countries in the same region*

***Assumed same standard deviation as for other region on the same continent,*
as China and United States have no proxy countries and a standard deviation could thus not be computed

Figure A.6: Comparison of board ages across regions (assumed normal distribution) (Source: Author).



Company ownership

The parameter of *Ownership* is allocated to companies at the set-up of the model and is assumed to not change over time. Considering the time constraints of this research, a country-level distribution was used to allocate a form of ownership to each steelmaker. More specifically, companies were assigned to be privately owned, state operated or publicly listed based on a chance distribution. The chances for a company to be allocated a specific type of ownership differ per country and are listed in Table A.5. The use of these probabilities enables the model to include heterogeneity among the agents regarding ownership, in light of the constraints of the study. However, the accuracy of the used values is limited as they do not directly represent the steel industry and are somewhat outdated.

As was established in Section 3.3, the form of ownership can be beneficial or disadvantageous to corporate climate action depending on the circumstances. Such contextual factors are incorporated in the model by allocating an Environmental Performance Index score to each agent using a normal distribution. The exact process for this is described later.

Table A.5: Distribution of ownership types per proxy country

Region	**Country**	**Privately owned**	**State owned**	**Publicly traded**	**Source**
China	China	8.5%	84.1%	7.4%	G. S. Liu et al. (2003)
Other Asia	Japan	5%	5%	90%	La Porta et al. (1999)
	India*	30%	18.3%	51.7%	La Porta et al. (1999)
	South Korea	20%	15%	65%	La Porta et al. (1999)
EU	Germany	10%	25%	65%	La Porta et al. (1999)
	Italy	15%	40%	45%	La Porta et al. (1999)
	Spain	15%	30%	55%	La Porta et al. (1999)
Non-EU	Russia	34%	53%	13%	Chernykh (2008)
	Turkey	50%	18%	32%	Chernykh (2008)
	Ukraine*	30%	18.3%	51.7%	La Porta et al. (1999)
United States	USA	20%	0%	80%	La Porta et al. (1999)
Other-NA	Canada	25%	0%	75%	La Porta et al. (1999)
	Mexico	100%	0%	0%	La Porta et al. (1999)

Note: Privately owned companies were reported by La Porta et al. (1999) as 'Family' firms and publicly traded companies as 'Widely held' or 'Miscellaneous'.
**For both India and Ukraine no data was available to determine the proportional distribution of ownership forms across companies in the country. As such, the sample average given on page 492 of La Porta et al. (1999) was used for both countries.*

Company size

Since the modelled group of steel companies is a combination of two different samples, varying approaches were used to give agents a value for *Production_size.*

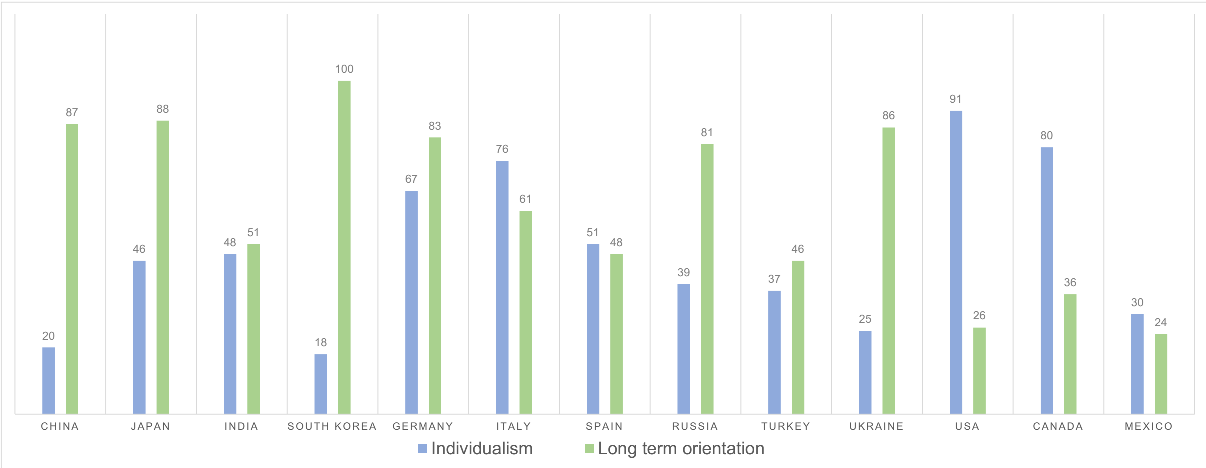
The companies that belong to the top 113 steel producers worldwide in 2021 have been given their actual production output in Mt for that year as value for *Production_size.* These numbers will not be listed here, but are available in Appendix E. As discussed previously, a number of companies was split based on the geographical location of generated revenues. This resulted in a number of companies with a smaller size that was still based on real world data. For some, the size may have been small enough to qualify as an SME, but it is assumed that this is not the case as SMEs are often defined based on employee numbers and not output values. Moreover, the splitting of companies is used to account more accurately for the global dispersion in production of the companies.

Other steelmakers included in the model (i.e. those not belonging to the before mentioned group but having a membership of WorldSteel - see Appendix E) received a value for *Production_size* based on a normal distribution. Specifically, the used normal distribution has a mean of 2Mt and a standard deviation of 0.3Mt. Following the empirical rule for normal distributions, 99.7% of all allocated company sizes should therefore be between 1.1Mt and 2.9Mt[6]. As such, the largest companies of this group stay smaller than the companies in the first group (i.e. the group of largest global steel producers). As the size of companies influences a number of factors relevant to potential SBT adoption, these companies are given a different size from the distribution in every simulation run.

Cultural aspects

In this study, two cultural dimensions from Hofstede are used to define the various steelmakers. The country specific scores for each of these dimensions are obtained from Insights (n.d.) and displayed in Figure A.7.

Figure A.7: National values for the used Hofstede dimensions (Source: data from Insights (n.d.)).



In order to adequately represent the differences in orientation among the agents, steelmakers have been assigned a score for each dimension based on the country level values. More concretely, values for the two dimensions were distributed using a normal distribution with the country level score as the mean and a standard deviation of 7.5 as in Kreulen et al. (2022).

[6]Though very unlikely, it is included in the model that companies cannot be allocated a negative value for *Production_size*. Instead, in the case this happens, the *Production_size* of that company is set to the smallest *Production_size* of all companies with a positive *Production_size*.

Stakeholder factors

Concerning the behaviour of competitors, the value for *Competitor_commitment* is determined as explained in Section 5.1.

Regarding the commitment of allies and social pressure exerted by stakeholders, the equations by which agents determine the value for each of these variables are also described in Section 5.1. Moreover, *Alliance_commitment* builds on the Hofstede dimension of 'individualism' for which the initialisation has been described in the subsection above. Stakeholder pressure is further influenced by firm size (also described in a previous subsection) and EPI, the latter of which will be elaborated on in Appendix A.5.

Financial performance

Generally, the financial performance of a company could be proxied by that company's net income. Due to time limitations, however, this study does not incorporate real financial data. Instead, companies are allocated a random value between 0 and 100 that represents their financial position. Considering that the financial performance of steelmakers generally varies per year (Figure A.8), the score for *Financial_performance* changes every year. More specifically, after the first score is given in the model initialisation, it will increase or decrease by four points every year. The direction of the four point change is random. As such, real world variability in firms' financial performance is considered, while it is not attempted to actually predict future profits or losses for the steelmakers (Figure A.9).

Figure A.8: Net income and net income change for ArcelorMittal over the last ten years (Source: MarketScreener (n.d.[a]))

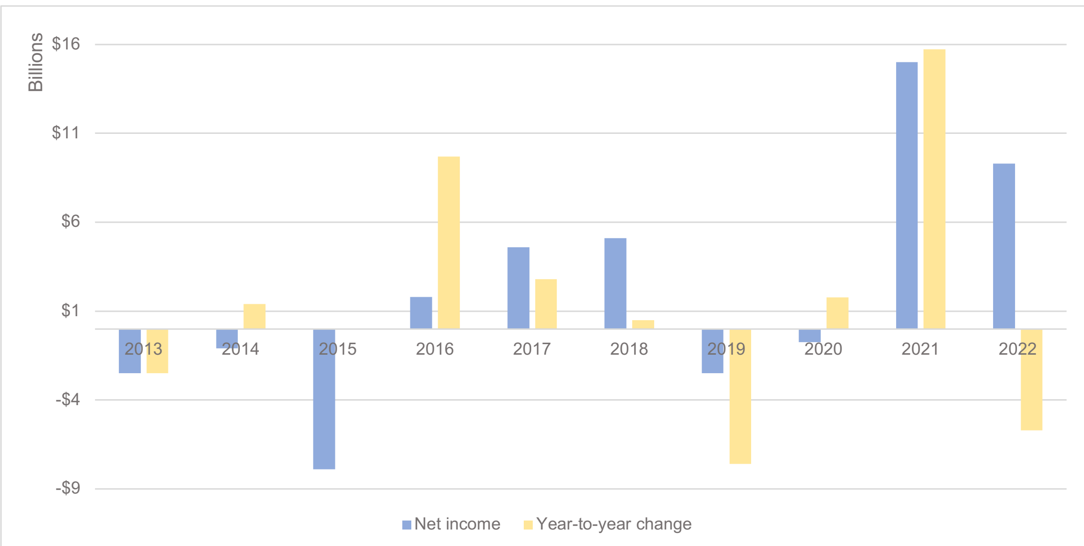
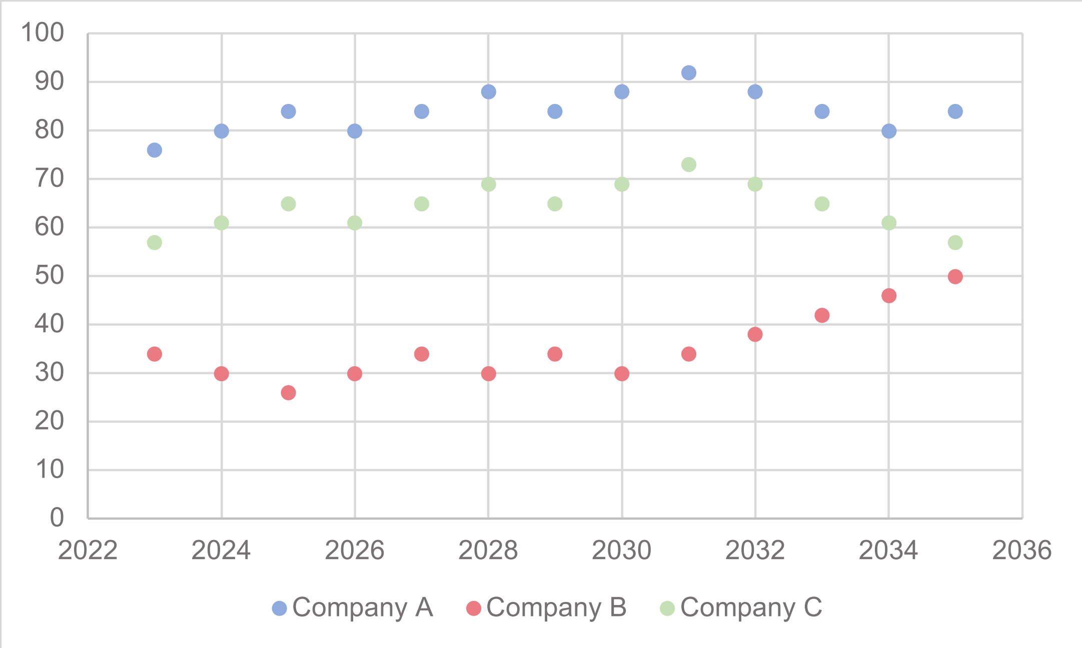


Figure A.9: Example of random *Financial_performance* progression in the model



Scrap intensity

In order to determine the scrap intensity (i.e. to what extent a company's steel-making process could use scrap as an input), it is necessary to estimate how much scrap there will be available over the time horizon of the model. Moreover, the projected steel production is needed in order to translate the amount of scrap available into an actual scrap intensity. The projected availability of scrap is obtained from Figure A.10, while the data on future production is estimated using Figure A.11. Note, however, that both projections use region aggregations different than the one in this study which entails that the determined scrap intensity is a very rough estimate. On top of that, estimations for the future are always inherently uncertain.

Figure A.10: Estimation of scrap availability for 2020 and 2050
(Source: adapted from WorldSteel (2021b)).

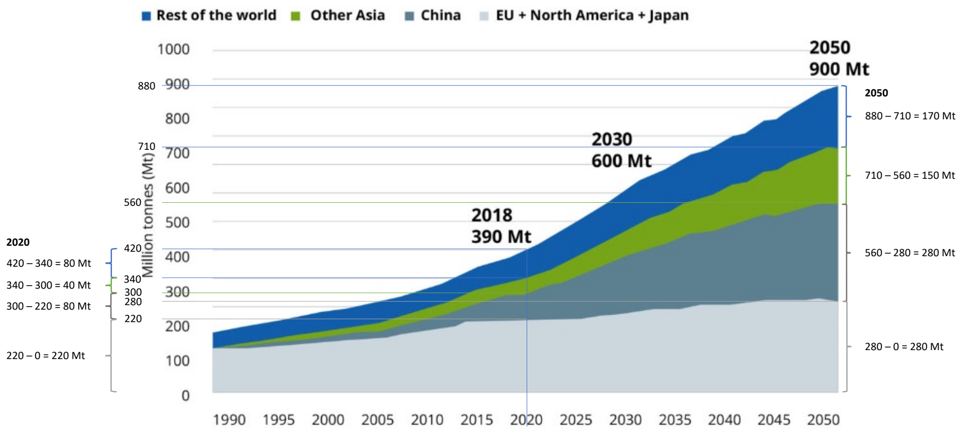


Figure A.11: Estimate of the future production quantities of crude steel
(Source: World Steel Dynamics (2020)).

World Steel Dynamics' Preliminary Crude Steel, BOF, EAF & DRI Forecast 2050
(million metric tonnes)

	2019						2050e						Change from 2019		
	Year	BOF	EAF	DRI	BOF %	EAF%	Year	BOF	EAF	DRI	BOF %	EAF%	BOF	EAF	DRI
Advanced Countries	**458**	**273**	**186**	**5**	**59**	**41**	**435**	**194**	**241**	**37**	**45**	**55**	**-79**	**55**	**32**
Japan	100.0	76.0	24.0	0.0	76.0	24.0	85.0	50.0	35.0	3.0	58.8	41.2	-26.0	11.0	3.0
South Korea	73.0	49.0	24.0	0.0	67.1	32.9	90.0	50.0	40.0	6.0	55.6	44.4	1.0	16.0	6.0
Western Europe	133.0	80.0	53.0	0.5	60.2	39.8	120.0	50.0	70.0	15.0	41.7	58.3	-30.0	17.0	14.5
United States	87.0	27.0	60.0	3.2	31.0	69.0	80.0	20.0	60.0	10.0	25.0	75.0	-7.0	0.0	6.8
Small Cap. Adv.	65.0	40.5	24.5	1.4	62.3	37.7	60.0	24.0	36.0	3.0	40.0	60.0	-16.5	11.5	1.6
China*	**996**	**889**	**107**	**0**	**89**	**11**	**800**	**600**	**200**	**100**	**75**	**25**	**-289**	**93**	**100**
Rest of the World	**419**	**194**	**225**	**103**	**46**	**54**	**652**	**330**	**322**	**135**	**51**	**49**	**137**	**97**	**32**
Africa	4.0	1.6	2.4	0.7	40.0	60.0	11.0	3.0	8.0	10.0	27.3	72.7	1.4	5.6	9.3
Brazil	32.8	25.6	7.2	0.0	78.0	22.0	41.0	28.0	13.0	3.0	68.3	31.7	2.4	5.8	3.0
CIS	98.0	66.0	32.0	8.0	67.3	32.7	115.0	65.0	50.0	17.0	56.5	43.5	-1.0	18.0	9.0
Eastern Europe	18.0	6.8	11.2	0.0	37.8	62.2	20.0	3.0	17.0	5.0	15.0	85.0	-3.8	5.8	5.0
Developing Asia	36.3	13.8	22.5	0.6	38.0	62.0	75.0	30.0	45.0	7.0	40.0	60.0	16.2	22.5	6.4
India	110.0	49.0	61.0	33.7	44.5	55.5	250.0	170.0	80.0	20.0	68.0	32.0	121.0	19.0	-13.7
Latin America	37.5	16.5	21.0	9.8	44.0	56.0	40.0	15.0	25.0	10.0	37.5	62.5	-1.5	4.0	0.2
MENA	48.3	2.4	45.9	50.1	5.0	95.0	55.0	3.0	52.0	60.0	5.5	94.5	0.6	6.1	9.9
Turkey	33.7	11.8	21.9	0.0	35.0	65.0	45.0	13.0	32.0	3.0	28.9	71.1	1.2	10.1	3.0
World Total	**1,873**	**1,355**	**518**	**108**	**72**	**28**	**1,887**	**1,124**	**763**	**272**	**60**	**40**	**-231**	**245**	**164**
World Ex-China	877	466	411	108	53	47	1,087	524	563	172	48	52	58	152	64

Source: WSD Estimates, WSA
**Includes WSD's estimates for induction furnace production*

By using the values from the figures above and combining them with real world production amounts from WorldSteel (n.d.), the scrap intensity can be calculated (Table A.6). The development of the *Scrap_intensity* over time is then assumed a linear process.

Table A.6: Estimated scrap intensity for present and future
(Source: data from WorldSteel (n.d.) and World Steel Dynamics (2020))

	2020			2050			2023	Bi-weekly
Region	**Scrap available (Mt)**	**Output (Mt)**	**Scrap intensity (%)**	**Scrap available (Mt)**	**Output (Mt)**	**Scrap intensity (%)**	**Scrap intensity (%)**	**linear growth (%-point)**
China	80	1064.7	7.5	280	800	35	10.26	0.038
Other Asia	79.6	286.6	27.8	150	450	33.3	28.33	0.008
Europe	132.3	278.1	47.6	193.0	255	75.7	50.4	0.039
North America	48.1	101	47.6	60.5	80	75.7	50.4	0.039

Note: As data is not available for all the defined regions in this study, Europe represents both EU and non-EU, while North America represents both United States and Other-NA. From the World Steel Dynamics data (i.e. the 2050 estimated production), Europe is the aggregate of Western Europe, Eastern Europe and CIS region. The latter is included as the major producers in this region (Russia and Ukraine) are European. For North American 2050 production, only data was available for the United States and other Asia is a combination of the estimated production of South Korea, Japan, India and 'developing Asia'. Furthermore, a weighted average based on 2020 country production output was used to divide the 2020 and 2050 scrap availability of 'EU + North America + Japan' over Other Asia (incl. Japan), Europe and North America.

Low-carbon electricity

The access of companies to low-carbon electricity is determined by assessing the share of renewables in the proxy countries' electricity grids. Moreover, the Global Renewables Outlook for 2050 by the International Renewable Energy Agency (IRENA (2020)) was used to estimate future availability of green electricity. The current availability of renewables and future projections are outlined in Table A.7.

Table A.7: Shares of renewables in countries' electricity mix (Source: IRENA (2020))

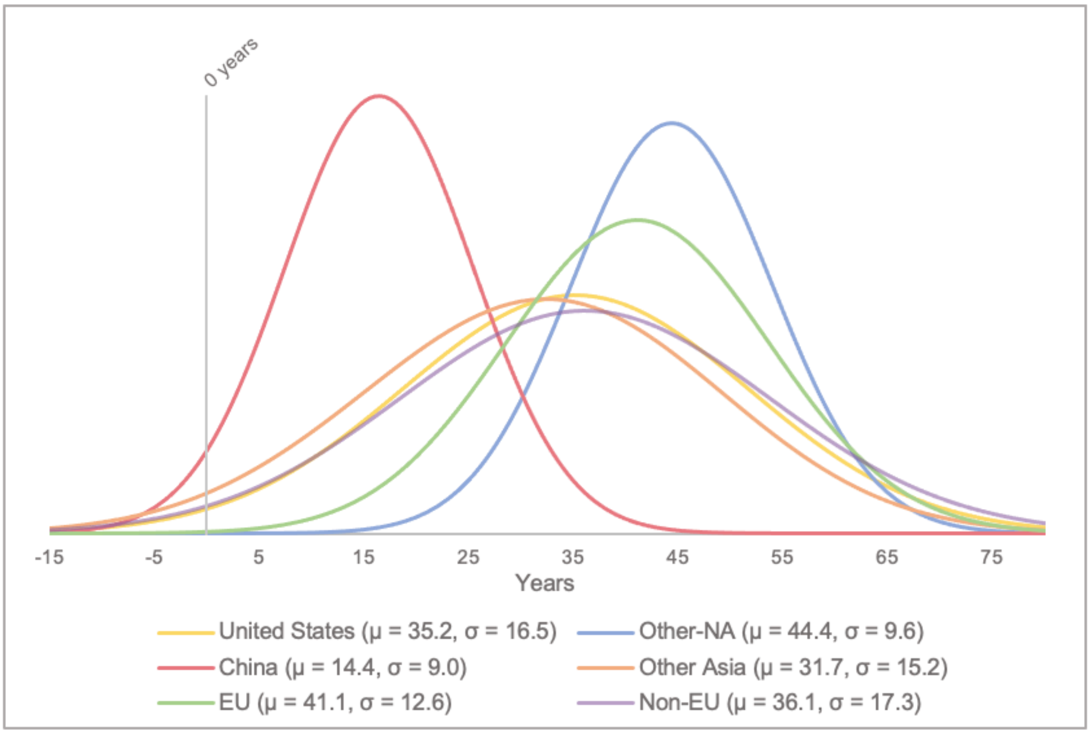
Country	2022 share of renewables (%)	2050 share of renewables	Bi-weekly linear growth (%-point)
China	36	90	0.084
Japan	29	85	0.086
India	23		0.096
South Korea	37		0.074
Germany	49.2	86	0.057
Italy	32		0.084
Spain	63		0.036
Russia	39	82	0.067
Turkey	42		0.062
Ukraine	75		0.011
USA	40	85	0.069
Canada	83	85	0.004
Mexico	26		0.092

Note: The 2022 share of renewables is used as the starting value for the share of renewables in 2023. Moreover, 2050 shares are estimated per region, while there may be large differences per region. As such, for example, Canada will only increase its share of renewables by 2%-point until 2050 while Mexico will grow it by 59%-point.

The age of steel-making capacity

As all modelled steelmakers have multiple production plants with different capacities and ages, a data set from the Global Energy Infrastructure Database (GID (n.d.)) was used instead of assessing all companies individually. The data from GID (n.d.) had already been grouped per region, though a different region distribution is used than in this study. For every region, it provides the amount of steel-making capacity with a certain age that exists. Using that, a weighted average and standard deviation were computed in Excel. It was then assumed that the capacity-age distribution was normally distributed, in order to define average asset age in the model (Figure A.12).

Figure A.12: Normal distribution of the age of steel-making capacity across regions (Source: based on data from GID (n.d.)).



Note: Data from the Global Energy Infrastructure Database, aggregated per region using a weighted average and weighted standard deviation with weights based on the amount of capacity with a certain age. To aggregate the data for the studied regions, Other-NA is proxied by Canada only, the EU by 'Western Europe', Non-EU by Russia and 'Eastern Europe' and Other Asia by India and 'East Asia'. Intervals in the database were represented by the average age of the interval (e.g. all capacity in the interval of 0-5 years of age was assumed 2.5 years old) and capacity ages were assumed to follow a normal distribution. Negative ages are in the model treated as the lowest interval (i.e. 2.5 years old).

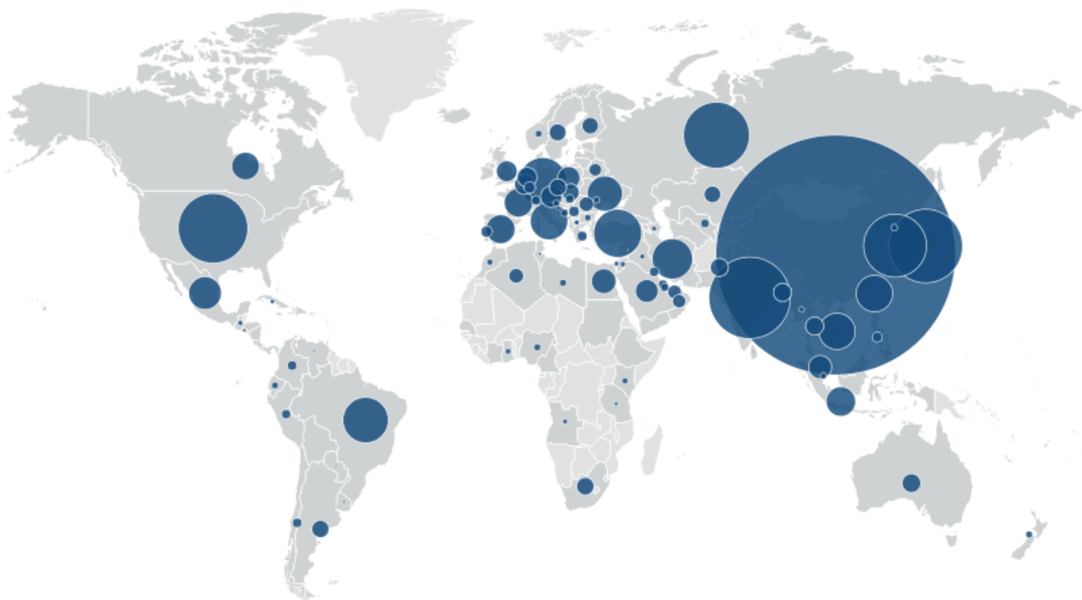
Background data

Some of the computations made or scores given depend on more information than provided in the previous subsections. What exact data is used for these variables and parameters is discussed here.

Production numbers

In order to sometimes determine weighted averages, the output values for different countries in 2021 were used. These values were always obtained from WorldSteel (n.d.), which specifies the crude steel production over the past years per country. Additionally, when regional totals were necessary in a computation, the values provided by Eurofer (2022) were used (see Figure 1.2).

Figure A.13: Country level steel production in 2021 (Source: WorldSteel (n.d.)).



Revenue data

For the splitting of the largest companies in regional 'subsidiaries', accurate revenue proportions per geographical region were needed. These were obtained from MarketScreener (n.d.[b]), which outlines the sales per region for the largest steel companies.

Environmental Performance Index

As has been mentioned before, the Environmental Performance Index (EPI) is used for a number of variables to determine the stance of a company or country towards the environment. A high EPI signals that a company is environmentally aware and conscious, while a low EPI suggests that it does not care too much about the topic. The values per country were acquired from the Yale Center for Environmental Law & Policy and Columbia University's Center for International Earth Science Information Network Earth Institute for 2022 (Table A.8). Since the model simulates a future time-frame, it was assumed that the EPI for each country (and indirectly each company) stays stable until 2036.

Table A.8: Environmental Performance Index scores per country for 2022 (Source: Wolf et al. (2022)).

Region	**Country**	**EPI**
China	China	28.4
Other Asia	Japan	57.2
	India	18.9
	South Korea	46.9
EU	Germany	62.4
	Italy	57.7
	Spain	56.6
Non-EU	Russia	37.5
	Turkey	26.3
	Ukraine	49.6
United States	USA	51.1
Other-NA	Canada	50.0
	Mexico	45.5

A.6 Description of sub-models

The last step in the model description using the ODD protocol is to describe the sub-models of the decision-making process. These are in detail explained in Section 5.1.

Appendix B

Weights

In order to determine the values for 'attitude', 'subjective norm' and 'behavioural control', companies compute the weighted sum of the scores of all relevant variables and parameters. The weights that are used in the base model are presented and discussed in this appendix. Challenging for accurate determination of the variable weights is that literature quantifying the effect sizes of the numerous factors hypothesised to influence a company's SBT-related decision-making is unavailable. As a consequence, the defined weights for the included variables and parameters are based on a combination of literature interpretation and personal communication with the Science Based Targets initiative's steel team. Moreover, since Chapter 3 outlines and discusses the drivers and barriers for which a weight is presented here, this appendix will not repeat such a discussion. Rather, complementary findings are discussed that help define accurate weights in complement to the discussion in Section 3.3. The then defined weights are listed in Table B.1.

- ***Board_diversity*** - Van Hilten (2022) finds both quantitative and qualitative evidence that the diversity of a firm's corporate board influences that firm's likelihood of joining the SBTi. More concretely, the author concludes that multiple forms of diversity (both gender and nationality) result in a higher probability of setting SBTs. Zaid et al. (2020) furthermore argue that international board members in general positively influence a business' corporate sustainability performance. In a similar line, Ruigrok et al. (2007) suggest that having a board in which women are adequately represented results in better environmental decision-making.
- ***Board_size_pressure*** - Van Hilten (2022) also concludes that there is both quantitative and qualitative evidence suggesting that larger firms are more likely to commit to the SBTi. In order to incorporate this in the model, the importance of *Board_size_pressure* is increased, as a company's board size is modelled to depend on that company's actual size. Lyon et al. (2019) further show that bigger companies are more probable to undertake pro-climate efforts.

- ***Board_age_pressure*** - Though Van Hilten (2022) did not directly find that the age of directors is influential in a company's SBT decision-making process, the author did conclude that (climate) leadership and progressiveness are important. It is assumed that this is more represented in younger boards, hence this variable is important to a certain extent.
- ***Ownership_pressure*** - Van Hilten (2022) argues that investors, as stakeholders, are very important for companies to decide on adopting SBTs. Okereke (2007) expands on this by arguing that pressure exerted by investors is one of the main drivers for corporate climate action. Lyon et al. (2019) moreover describe investor pressure as a significant source of external influence on firms. Lastly, personal communication with the SBTi steel team resulted in the influence of investors also being mentioned as imperative (Khan et al., 2023).
- ***Price_pressure*** - Though Van Hilten (2022) focuses on internal characteristics of companies when assessing which factors drive their commitment behaviour, carbon pricing is also believed an important lever to spur company climate action. More concretely, experts believe that - at least in the EU - carbon pricing is the main driver for emissions abatement (Refinitiv, 2022). Additionally, Khan et al. (2023) argue that cost is an important focus for (steel) companies committing to the SBTi.

- ***Scrap_intensity*** - Using scrap is in many cases one of the most effective and easy ways to reduce steelmaking emissions (IEA, 2020). However, the availability of (high quality) scrap is a limiting factor (Hoffmann et al., 2020), making it important for companies to assess what part of their production they could fulfill using secondary inputs.
- ***Renew_electricity*** - Similar to scrap, the availability of low-carbon electricity is a limiting factor of decarbonisation in the steel industry (Hoffmann et al., 2020). Still, if available, it could enable companies to reduce emissions through the use of EAF with renewables and later on by using for example green hydrogen.
- ***Asset_age_opportunity*** - Investment cycles in the steel industry are long and the assets used have very long lifetimes. As a result, it is hypothesised that companies find it important to assess the number of opportunities they will have to deeply decarbonise in the near future.
- ***Financial_performance*** - Steel firms are believed to be cost focused - with exceptions of more specialised companies - and Section 3.3 showed that companies mostly want to take the risks associated with decarbonisation only when the financial risk is not too high.

- ***Alliance_commitment*** - Since alliances also exist in the real world, it was assumed that steel companies are to a certain extent interested in what others in the industry are doing.
- ***Competitor_commitment*** - Van Hilten (2022) shows that competitiveness is an important aspect for companies when it regards their SBT adoption decision. This is substantiated by Khan et al. (2023), who argue that one important reason for companies committing to the SBTi is that it betters their competitive edge in the market.
- ***Stakeholder_pressure*** - Van Hilten (2022) finds qualitative evidence that pressures exerted by stakeholders are important for companies in their decision-making process regarding the setting of SBTs. This is supported by findings from Okereke (2007) and Lyon et al. (2019), who suggest that the environmental stance of stakeholders can substantially influence a company's climate action.

Table B.1: Weights used in the baseline model

Attitude		**Subjective norm**		**Behavioural control**	
Factor	**Weight**	**Factor**	**Weight**	**Factor**	**Weight**
Board_diversity	0.25	*Alliance_commitment*	0.20	*Scrap_intensity*	0.25
Board_size_pressure	0.15	*Competitor_commitment*	0.40	*Renew_electricity*	0.25
Board_age_pressure	0.125	*Stakeholder_pressure*	0.40	*Asset_age_opportunity*	0.20
Ownership_pressure	0.2			*Financial_performance*	0.30
Price_pressure	0.275				
Total	**1**	**Total**	**1**	**Total**	**1**

Appendix C

Sensitivity results

Figure C.1: Effect of altering the value for *Create_links*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

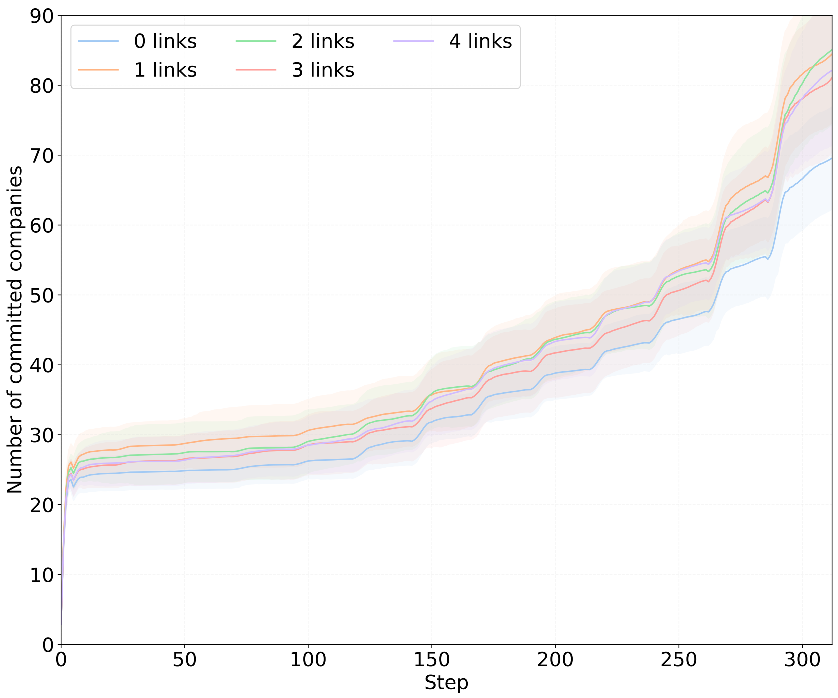


Figure C.2: Effect of altering the value for *Financial_performance_change*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

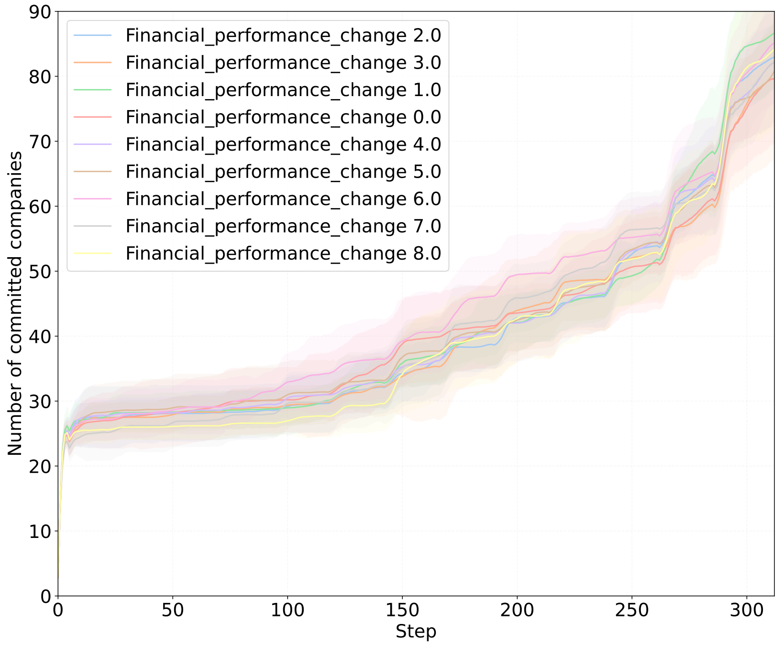


Figure C.3: Effect of altering the value for *Large_size_threshold*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

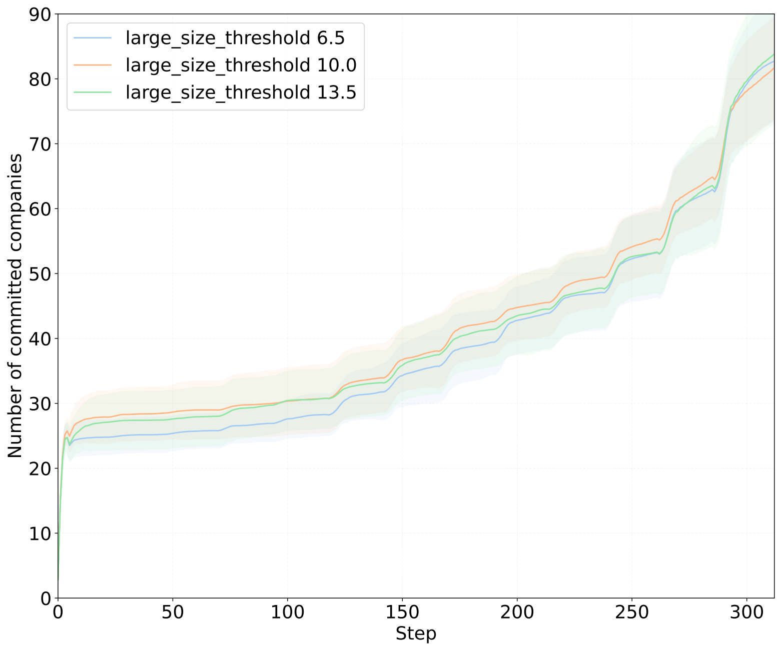


Figure C.4: Effect of altering the value for *Medium_size_threshold*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

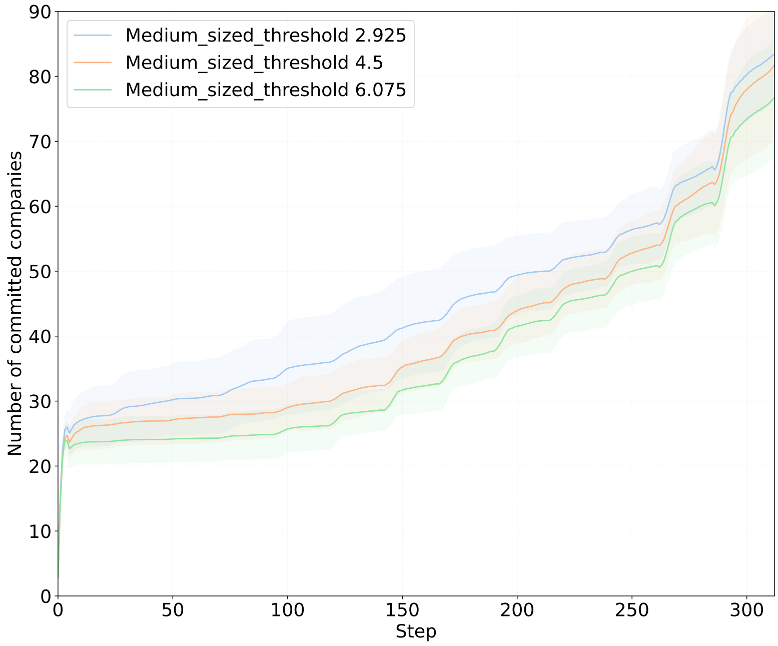


Figure C.5: Effect of altering the value for *Price_threshold*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

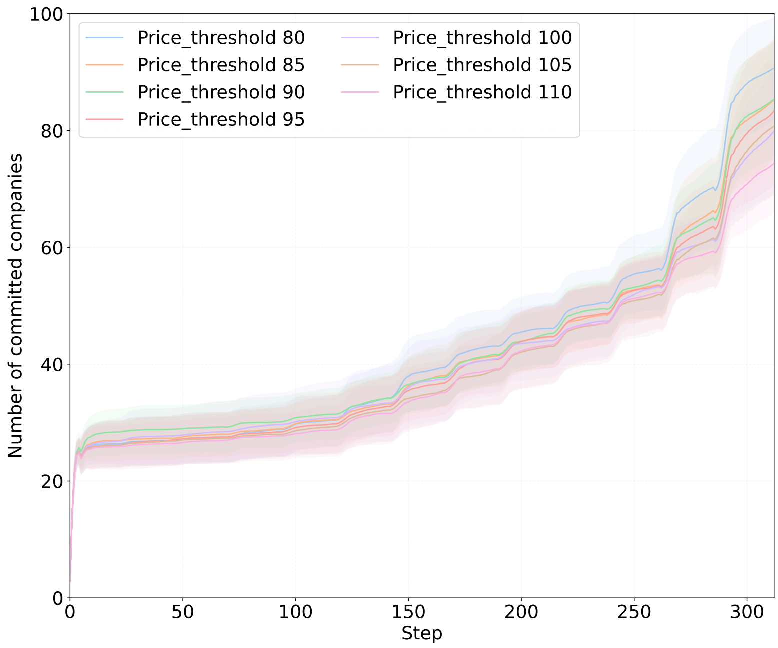


Figure C.6: Effect of altering the value for *Size_effect_board*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

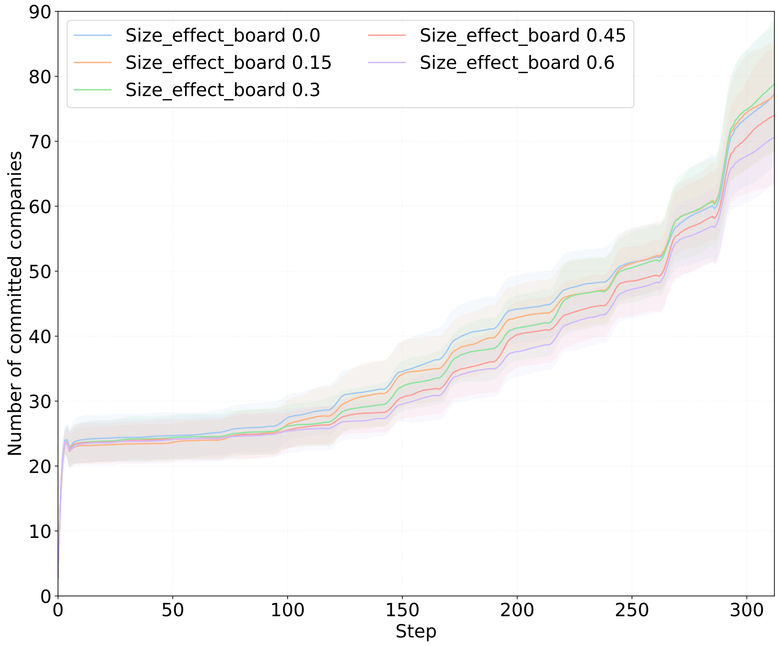


Figure C.7: Effect of altering the value for *Size_effect_diversity*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation

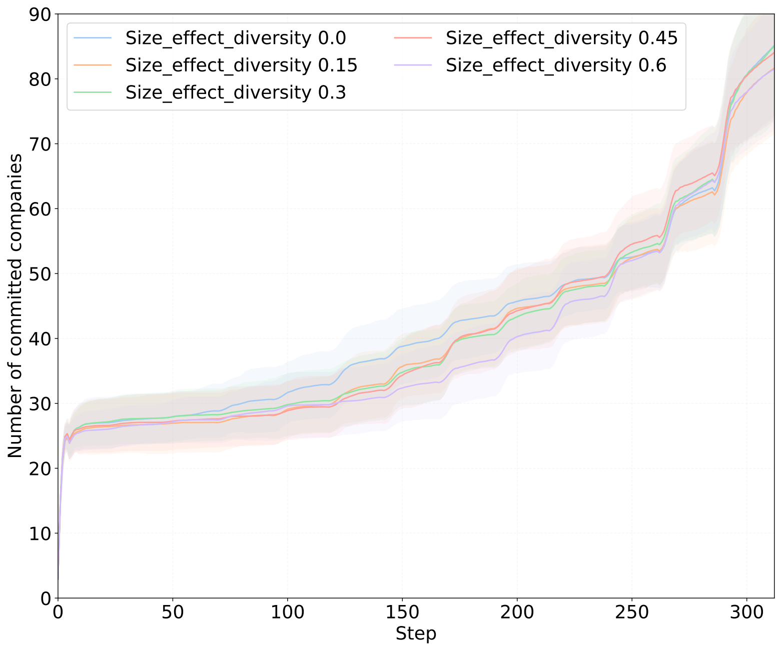
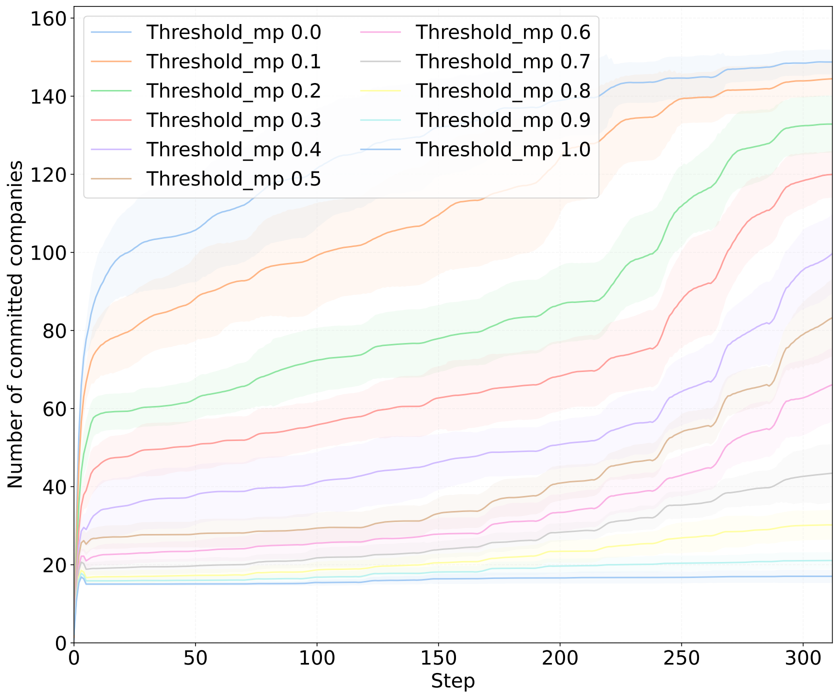


Figure C.8: Effect of altering the value for *Threshold_mp*

Note that the lines depict the mean number of commitments per step, whereas the shaded areas depict the mean +/- one standard deviation



Appendix D

Variables and parameters

This appendix provides two tables with the main global and company-specific variables and parameters of the model. Details on the data behind many of the variables can be found in Appendix A, while others are computed in the model.

Figure D.1: Overview of the most relevant global variables and parameters of the model

Parameter/variable*	**Type**	**Value [range]****	**Description*****
year	integer	[2023; 2035]	Current year of the model
year_start	integer	2023	Start year of the model
month	integer	[1; 12]	Current month of the model
companies_total	integer	163	Number of modelled companies
companies_region	integer	[7; 68]	Number of companies per region
companies_continent	integer	[15; 100]	Number of companies per continent
continent_committed_competitors_size	integer	[0; 100]	Number of committed companies for a particular competitor group (defined by continent and size)
country_epi	float	[0; 100]	Environmental Performance Index of a specific country
country_epi_max	float	62.4	Highest EPI of a modelled country
company_epi_max & company_epi_min	float	[0; 100]	Highest/lowest EPI of a modelled company
company_size_max	float	119.95	Size of the largest company
size_mp_large, size_mp_medium, size_mp_small	float	0.5, 1, 1.5	Multiplier used to incorporate visibility
variable_w (e.g. board_diversity_w)	float	[0; 1]	Weight assigned to each main variable
board_age_max	float	[0; ∞]	Highest average board age
board_age_min	float	[0; ∞]	Lowest average board age
board_size_max	integer	[1; ∞]	Largest modelled board
board_size_min	integer	1	Smallest modelled board
carbon_price_slope_country	float	[0; ∞]	Slope that allows the carbon price to increase linearly over time
carbon_price_start_country	float	[0; ∞]	Value for the carbon price in a country at model start
price_threshold	integer	95	Limit at which p*rice_pressure* is max
free_allowances_country	float	[0; 1]	Share of emission allowances allocated for free per country (1 = 100%)
free_allowances_decrease_country	float	[0; 1]	Signals by how much the share of free allowances in a country decreases per year (1 = 100%)
carbon_price_country	float	[0; ∞]	Carbon price in a country
individualism	integer	[0; 100]	Hofstede value for individualism, per country
long_term_orientation	integer	[0; 100]	Hofstede value for long term orientation, per country
renew_elec_start	float	[0; 100]	Initial share of electricity mix that is renewable, per country
renew_elec_growth	float	[0; 100]	Percentage point increase of renewables in electricity mix, per country
si_start	float	[0; 100]	Initial share of production possible using scrap input, per country
si_growth	float	[0; 100]	Percentage point increase of scrap intensity, per country
create_links	integer	2	Number of random connections each company is asked to make
size_effect_diversity	float	0.3	Effect of company size on board diversity
size_effect_board	float	0.3	Effect of company size on number of directors
lower_state_threshold	integer	45	Threshold separating weak environmental performance (<) from medium environmental performance, for state-owned companies
upper_state_threshold	integer	55	Threshold separating medium environmental performance (<) from strong environmental performance, for state-owned companies
listed_threshold	integer	55	Threshold separating medium environmental performance (<) from strong environmental performance, for listed companies
mp_high, mp_mid & mp_low	float	1, 0.9, 0.8	Multiplier used to alter *ownership_pressure* in accordance with a company's environmental performance and ownership
asset_lifetime	integer	25	Lifetime (years) of steelmaking capacity
financial_performance_change	integer	4	Value by which a company's financial performance changes annually
large_size_threshold	float	10	Minimum size threshold for large companies (Mt)
medium_size_threshold	float	4.5	Minimum size threshold for medium companies (Mt)
standard_threshold	integer	38	Base threshold used by companies to determine the level of attitude, subjective norm and behavioural control needed before they develop intention and/or translate that intention into actual commitment
threshold_mp	float	0.5	Multiplier used to scale down the effect of a company's long-term orientation on that company's *long_term_threshold*

**Only the most relevant global variables and parameters are listed in the table. All others can be found in the supplementary Netlogo model.*

***Since some variables are aggregated, the nominal value is only indicated where possible. For the other base values, please refer to Appendix A.*

****Many of the variables are computed in the model. For the sources on what they are based, please refer to Appendix A*

Figure D.2: Overview of the most relevant company-specific variables and parameters of the model

Parameter/variable*	**Type**	**Value [range]**	**Description****
production_size	float	[0; 119.95]	Size of a company in output (Mt)
size_classification	string	Large, Medium, Small	Assigned size category
relative_size	float	[0; 100]	Company size expressed as a share of the largest company's size
continent	string	Asia, Europe, North America	Continent of location
region	string	see Scope	Region of location
country	string	see Scope	Country of location
board_age	float	[0; ∞]	Average age of the board
board_size	integer	[1; ∞]	Number of directors
board_age_pressure	float	[0; 100]	A company's score relating to *board_age* that counts towards 'attitude'
board_size_pressure	float	[0; 100]	A company's score relating to *board_size* that counts towards 'attitude'
share_female	float	[0; 100]	Share of board that is female
board_diversity	float	[0; 100]	Represents how diverse the board is
ownership	string	listed, private, state	Form of ownership the company has
ownership_mp	float	[0; 1]	Multiplier incorporating a company's ownership and environmental performance
ownership_pressure	float	[0; 100]	Represents the pressure owners exert on a company to commit
hof_ind	float	[0; 100]	Company score for Hofstede's individualism dimension
hof_long	float	[0; 100]	Company score for Hofstede's long term orientation dimension
financial_performance	integer	[0; 100]	Normalised score for financial performance
perceived_price	float	[0; ∞]	Price of GHG emissions after incorporating freely received allowances
price_pressure	float	[0; 100]	Pressure exerted by carbon pricing towards commitment
scrap_intensity	float	[0; 100]	Estimated share of production possible using scrap input
renew_electricity	float	[0; 100]	Initial share of relevant electricity mix that is renewable
asset_age_start	float	[0; ∞]	Average age of steelmaking capacity at model start
asset_age_opportunity	integer	50, 100	Score representing the number of overhaul opportunities before 2050
competitor_commitment	float	[0; 100]	Pressure exerted by competitors towards commitments
company_epi	float	[0; 100]	Environmental performance proxy of company
country_pressure	float	[0; 100]	Used to incorporate a company's country of operation in the equation for *stakeholder_pressure*
stakeholder_pressure	float	[0; 100]	Pressure exerted by general stakeholders towards commitment
committed_allies	integer	[0; *number_allies*]	Number of allies that are committed
alliance_commitment	float	[0; 100]	Pressure exerted by allies towards commitment
number_allies	integer	[0; 162]	Number of allies
commitment_status	binary	0, 1	Signal to incorporate if a company is already committed
boardmeeting	binary	TRUE, FALSE	Used to identify if a company has a board meeting
attitude	float	[0; 100]	Weighted average of variables relating to TPB construct 'attitude'
subjective_norm	float	[0; 100]	Weighted average of variables relating to TPB construct 'subjective norm'
behavioural_control	float	[0; 100]	Weighted average of variables relating to TPB construct 'behavioural control'
long_term_threshold	float	[0; 100]	Main threshold used by companies in their decision-making
intention	binary	TRUE, FALSE	Stores if a company already has developed intention
positive_attitude	binary	TRUE, FALSE	Stores if a company has a positive attitude
positive_subjective_norm	binary	TRUE, FALSE	Stores if a company feels sufficient social pressure
positive_behavioural_control	binary	TRUE, FALSE	Stores if a company feels able to achieve potential SBTs

**Only the most relevant company specific parameters and variables are listed in the table. All others can be found in the supplementary Netlogo model.*

***Many of the variables are computed in the model. For the sources on what they are based, please refer to Appendix A.*

Appendix E

Companies

Notes to the figures:

Companies coloured in green are committed in the real world at the start of 2023.

* The ownership of all companies producing 12 or more Mt was assessed to conclude if a company is state-owned or not. When it was clear that a company is state-owned, it was assumed that the full production of this company happens in the country of its headquarters. For all other companies producing 12 or more Mt, sales data were used to make an estimate of the geographical dispersion of operations. If more than 60% of revenue came from one region, the company was not split. In all other cases, the company was split in accordance with the geographical distribution of its revenue.

** If the headquarters of a company is not in one of the proxy countries, one of the proxy countries of the company's respective region is assigned to the company as explained under 'scales' in Appendix A.2.

*** Due to the unavailability of data, it was assumed that this company operates fully in the country of its headquarters. Since data was only absent for Chinese companies, and La Porta et al. (1999) show that more than 80% of companies in China are state-owned, the assumption was made that all these companies are operated by the Chinese state.

**** All companies that are not included in the steel companies producing more than 3Mt were allocated a production size in the model as explained in Appendix A.5.

Figure E.1: Companies included in the model - part I

Companies*	Headquarters	Production (Mt)	Region	Country**
China Baowu Group (1)	China	119.95	China	China
ArcelorMittal - United States	NA	9.27	United States	United States
ArcelorMittal - Other-NA	NA	7.37	Other-NA	Canada
ArcelorMittal - EU	NA	37.81	EU	Italy
ArcelorMittal - Non-EU	NA	8.88	Non-EU	Turkey
ArcelorMittal - Other Asia	NA	1.74	Other Asia	India
Ansteel Group (3)	China	55.65	China	China
Nippon Steel Corporation (4)	Japan	49.46	Other Asia	Japan
Shagang Group	China	44.23	China	China
POSCO	South Korea	42.96	Other Asia	South Korea
HBIS Group	China	41.64	China	China
Jianlong Group***	China	36.71	China	China
Shougang Group	China	35.43	China	China
Tata Steel Group - EU	NA	5.63	EU	Italy
Tata Steel Group - Non-EU	NA	5.63	Non-EU	Ukraine
Tata Steel Group - Other Asia	NA	18.90	Other Asia	Japan
Shandong Steel Group	China	28.25	China	China
Delong Steel Group***	China	27.82	China	China
JFE Steel Corporation	Japan	26.85	Other Asia	Japan
Valin Group	China	26.21	China	China
Nucor - United States	NA	18.67	United States	United States
Nucor - Other-NA	NA	6.98	Other-NA	Mexico
Fangda Steel	China	19.98	China	China
Hyundai Steel	South Korea	19.64	Other Asia	South Korea
Liuzhou Steel	China	18.83	China	China
JSW Steel Limited	India	18.59	Other Asia	India
Steel Authority of India Ltd. (SAIL)	India	17.33	Other Asia	India
NLMK - United States	NA	2.68	United States	United States
NLMK - Other-NA	NA	1.00	Other-NA	Canada
NLMK - EU	NA	3.03	EU	Spain
NLMK - Non-EU	NA	7.09	Non-EU	Russia
NLMK - Other Asia	NA	0.59	Other Asia	South Korea
Baotou Steel	China	16.45	China	China
United States Steel Corporation - US	NA	9.45	United States	United States
United States Steel Corporation - Other-NA	NA	3.54	Other-NA	Canada
United States Steel Corporation - EU	NA	3.28	EU	Italy
Cleveland-Cliffs - United States	NA	14.88	United States	United States
Cleveland-Cliffs - Other-NA	NA	1.42	Other-NA	Canada
China Steel Corporation	Taiwan, China	15.95	China	China
Jingye Group***	China	15.38	China	China
Sinogiant Group***	China	14.34	China	China
CITIC Pacific	China	13.97	China	China
Magnitogorsk Iron & Steel Works (MMK)	Russia	13.59	Non-EU	Russia
Rizhao Steel***	China	13.57	China	China
EVRAZ - United States	NA	1.48	United States	United States
EVRAZ - Other-NA	NA	1.55	Other-NA	Mexico
EVRAZ - EU	NA	0.60	EU	Italy
EVRAZ - Non-EU	NA	5.63	Non-EU	Russia
EVRAZ - Other Asia	NA	2.43	Other Asia	Japan
EVRAZ - China	NA	1.85	China	China
Zenith Steel***	China	12.76	China	China
Shaanxi Steel	China	12.39	China	China
Tsingshan Holding	China	12.37	China	China
Shenglong Metallurgical	China	12.16	China	China
thyssenkrupp	Germany	12	EU	Germany
Severstal	Russia	11.65	Non-EU	Russia
Nanjing Steel	China	11.58	China	China
Metinvest Holding LLC	Ukraine	11.48	Non-EU	Ukraine
Sanming Steel	China	11.4	China	China
Donghai Special Steel	China	10.42	China	China
Xinyu Steel	China	10.14	China	China
Steel Dynamics, Inc.	USA	9.84	United States	United States
Anyang Steel	China	9.5	China	China
Erdemir Group	Turkey	9.02	Non-EU	Turkey
Jiuquan Steel	China	8.75	China	China
SSAB	Sweden	8.18	EU	Germany
Jindal Steel and Power Ltd (JSPL)	India	7.98	Other Asia	India
voestalpine Group	Austria	7.86	EU	Italy
Yingkou Plate	China	7.75	China	China
Jiujiang Wire Rod	China	7.5	China	China
Jinxi Steel	China	7.46	China	China

Figure E.2: Companies included in the model - part II

Companies*	Headquarters	Production (Mt)	Region	Country**
Salzgitter Group	Germany	6.75	EU	Germany
Kobe Steel, Ltd.	Japan	6.75	Other Asia	Japan
Hoa Phat Steel	Vietnam	6.7	Other Asia	South Korea
CELSA Steel Group	Spain	6.59	EU	Spain
Formosa Ha Tinh	Vietnam	6.5	Other Asia	Japan
Shiheng Special Steel	China	5.95	China	China
Ganglu Steel	China	5.91	China	China
Puyang Steel	China	5.89	China	China
RIVA Group	Luxembourg	5.71	EU	Spain
Commercial Metals Company	USA	5.66	United States	United States
Binxin Special Steel	China	5.66	China	China
Gaoyi Steel	China	5.64	China	China
Rashtriya Ispat Nigam Ltd (VIZAG Steel)	India	5.59	Other Asia	India
Lingyuan Steel	China	5.41	China	China
Jinnan Steel	China	5.35	China	China
Yuanli Group	China	4.94	China	China
Ruifeng Steel	China	4.92	China	China
Metalloinvest Management Company	Russia	4.9	Non-EU	Russia
Jincheng Fusheng	China	4.88	China	China
Aosen Steel	China	4.83	China	China
Tianzhu Steel	China	4.77	China	China
Hongxing Steel	China	4.72	China	China
Tosyalı Holding	Turkey	4.68	Non-EU	Turkey
Huttenwerke Krupp Mannesmann	Germany	4.62	EU	Germany
Habaş	Turkey	4.54	Non-EU	Turkey
Xinxing Pipes	China	4.53	China	China
Donghua Steel	China	4.31	China	China
Rockcheck Steel	China	4.3	China	China
Xinda Steel	China	4.2	China	China
TMK	Russia	4.14	Non-EU	Russia
Ningbo Steel	China	4.05	China	China
Yuhua Steel	China	4	China	China
Jianbang Group	China	3.94	China	China
Jiyuan Steel	China	3.91	China	China
Dongkuk Steel Mill Co., Ltd.	South Korea	3.88	Other Asia	South Korea
Lianxin Steel	China	3.84	China	China
Sanbao Steel	China	3.8	China	China
Yukun Steel	China	3.72	China	China
Desheng Group	China	3.64	China	China
Xinyang Steel	China	3.63	China	China
Zhongyang Steel	China	3.56	China	China
Mechel	Russia	3.54	Non-EU	Russia
İçdaş	Turkey	3.53	Non-EU	Turkey
Acciaieria Arvedi SpA	Italy	3.41	EU	Italy
Longteng Special Steel	China	3.36	China	China
Eastran Special Steel	China	3.31	China	China
Guigang Steel	China	3.29	China	China
Xuzhou Steel	China	3.21	China	China
Taishan Steel	China	3.15	China	China
Rongxin Steel	China	3.07	China	China
Xianfu Steel	China	3.01	China	China
Acciaieria Bertoli Safau SpA	Italy	NA****	EU	Italy
Acerinox S.A.	Spain		EU	Spain
Aichi Steel Corporation	Japan		Other Asia	Japan
Aperam	Belgium/France		EU	Germany
Arjas Steel Private Limited	India		Other Asia	India

Figure E.3: Companies included in the model - part III

Companies*	Headquarters	Production (Mt)	Region	Country**
Badische Stahlwerke GmbH	Germany		EU	Germany
Baku Steel Company CJSC	Azerbaijan		Other Asia	India
Bangladesh Steel Re-Rolling Mills	Bangladesh		Other Asia	South Korea
Böllinghaus GmbH	Germany		EU	Germany
Cogne Acciai Speciali SpA	Italy		EU	Italy
Colakoglu Metalurji	Turkey		Non-EU	Turkey
Daido Steel Co. Ltd.	Japan		Other Asia	Japan
Diler Iron & Steel Company Inc.	Turkey		Non-EU	Turkey
Duferco Participiations Holding S/A	Luxembourg		EU	Germany
Eramet	France		EU	Spain
Feng Hsin Steel Co., Ltd.	Taiwan, China		China	China
Grupo Acerero	Mexico		Other-NA	Mexico
PT Gunung Raja Paksi, Tbk	Indonesia		Other Asia	Japan
Kaptan Demir Celik Endustrisi ve Ticaret	Turkey		Non-EU	Turkey
Kroman Celik Sanayii	Turkey		Non-EU	Turkey
NatSteel Holdings Pte Ltd	Singapore		Other Asia	India
New Castle Stainless Plate, LLC	England		EU	Italy
Nippon Kinzoku	Japan		Other Asia	Japan
Nippon Yakin Kogyo Co., Ltd	Japan		Other Asia	Japan
Ovako AB	Sweden		EU	Germany
Sahaviriya Steel Industries Plc	Thailand		Other Asia	India
Sanyo Special Steel Co., Ltd	Japan		Other Asia	Japan
SeAH Besteel Corporation	South Korea		Other Asia	South Korea
Shabro Metallic Pvt. Ltd	India		Other Asia	India
Siam Yamato Steel Company Corporation	Thailand		Other Asia	South Korea
Sidenor S.A.	Greece		EU	Germany
SIJ (Slovenian Steel Group)	Slovenia		EU	Italy
Stahlbeteilungen Holding S.A.	Luxembourg		EU	Italy
Store Steel d.o.o.	Slovenia		EU	Spain
Sunflag Iron & Steel Co. Ltd.	Japan		Other Asia	Japan
Swiss Steel Group	Switzerland		EU	Germany
Ternium	Luxembourg		EU	Germany
Trinecke Zelezarny a.s.	Czech Republic		EU	Spain
Tung Ho Steel Enterprise Corporation	Taiwan, China		China	China
Visa Steel	India		Other Asia	India
Wei Chih Steel Industrial Co., Ltd	Taiwan, China		China	China