THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Transition to a low-carbon electricity system — investment decisions under heterogeneity, uncertainty and financial feedback

JINXI YANG

Department of Space, Earth, and Environment
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2021

Transition to a low-carbon electricity system — investment decisions under heterogeneity, uncertainty and financial feedback
JINXI YANG

Department of Space, Earth, and Environment
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone + 46 (0)31-772 1000

Printed Chalmers Reproservice
Gothenburg, Sweden 2021

Transition to a low-carbon electricity system — investment decisions under heterogeneity, uncertainty and financial feedback

JINXI YANG

Department of Space, Earth, and Environment
Chalmers University of Technology

Abstract

A transition to a low-carbon electricity system will require a substantial increase in the investment rate in low-carbon technologies. This calls for a better understanding of investment decisions and their impact on the pace of the transition. We explore the transition to a low-carbon electricity system by developing an agent-based model, focussing on agents' decisions when investing in new power plants.

This work addresses three characteristics associated with investment decisions—heterogeneity, uncertainty, and financial feedbacks—which many energy system models do not take into account.

In this study, heterogeneity is represented by the agents' different levels of risk aversion (represented by the hurdle rate employed by the agent) and their different expectations for the future carbon price.

Uncertainty is reflected by the agents' imperfect foresight. They have limited information on future electricity prices, carbon prices, electricity demand, etc. Also, there is stochasticity in fuel prices and electricity demand.

Financial feedback in the model is designed so that an agent's previous investment decisions will impact its future ability to invest. An agent's new investment impacts the capacity mix and electricity price, which, in turn, impact the revenue the agent receives. If the investment turns out to be profitable, then the agent has more capital to make further investments; if unprofitable, investing may be hampered in the future.

This study has analysed the transition on two levels—the system level and the level of the individual agents. On the system level, we explored system dynamics such as the development of the capacity mix, electricity price, and emission trajectories over time. We have also analysed the competition among low-carbon technologies, the value of wind, and returns on investments for different technologies. On the level of the individual agents, we investigate different investment criteria and outcomes.

Under a scenario with an increasing carbon tax, our model exhibits a transition to a low-carbon electricity system. Wind, together with gas-fired power plants, competes with nuclear power in the capacity expansion. The value of wind will drop relatively, but not absolutely.

On the agent level, results show that agents who use lower hurdle rates are more willing to make investments and therefore accelerate the transition. But as every investment is associated with risk, these agents also face a greater risk of going bankrupt, especially when they are less financially constrained. Agents who expect carbon prices that are too low or too high compared to the actual development also have a higher tendency to go bankrupt, and the return on equity for these agents is generally lower than for agents with a more accurate carbon price expectation.

This study illustrates the importance of including heterogeneity, uncertainty, and financial feedback in models of the energy transition. When the model is run with homogeneous agents or has different degrees of uncertainties, or no financial feedback mechanisms, results differ on both the system level and the level of the individual agents.

Keywords: electricity system transition, agent-based modelling, investment decisions, investment financing, capital availability, heterogeneous actors.

List of appended papers

Paper I

Yang, J., Azar, C., Lindgren, K., 2020. Modelling the transition towards a carbon-neutral electricity system - investment decisions and uncertainty. Submitted to *Energy Strategy Reviews*, under review.

CA and KL conceived the idea, with contributions from JY. CA, KL and JY developed the model. JY and KL implemented the model. All authors designed model experiments, analysed the results, and wrote the paper.

Paper II

Yang, J., Azar, C., Lindgren, K., 2021. Financing the transition of the electricity system – an agent-based approach to modelling the investment decisions. Submitted to *Frontiers in Climate*, under review.

KL and CA conceived the idea, with contributions from JY. KL, CA, and JY further developed the model. JY, CA and KL designed model experiments and analysed the results. JY wrote the paper with contributions from CA and KL.

Acknowledgements

I want to take this opportunity to express my genuine gratitude to people who in various ways have helped me on this half of my Ph.D. journey.

First and foremost, I would like to thank my two amazing supervisors—Kristian Lindgren and Christian Azar. Thank you for your steady guidance, great support, constructive feedback, and endless encouragement. I have grown so much, both professionally and personally. I am probably the most *HAPPI* Ph.D. student in our division[1].

Also big thanks to Daniel Johansson, Sonia Yeh, and Martin Persson, for your supervision and helpful advice.

Thanks to my friends and colleagues at FRT. Thank you for sharing your wisdom, enthusiasm for work, witty remarks, and practical life hacks. Thanks to Emma, Liv, Xiaoming, Ella, Yuan, Lola, Ahmet, Swapnil, Johannes, Andreas, Carolina, Susanne, Florence, Niklas, Stefan, Çaglar, Ankit, Martin, Wasim, Hanna, Rasmus, Riccardo, David, Christel, Claes, Frances, Fredrik, Lina, Göran, Jessica, John, Jörgen, Lorenzo, Markus, Sebnem, Niclas, Ulrika, Maria, Mairon, Erik, Vilhelm, Karl-Erik, Sten, Karin, and Anna. Thank you for making the work environment inspiring and enjoyable.

Thanks to my officemates Johan and Gavin for bringing in interesting conversation topics and playing the table tennis championship.

Thanks to our division head Jonas and our administrative assistant Angelica for your support and for helping create a smooth and pleasant work experience.

Thanks to Paulina for helpful comments.

Thanks to the ENSYSTRA project for providing the research funding and offering various training opportunities. I have benefited a lot from being a part of this project.

Last but not the least, I want to thank my family. As the famous aphorism says, "behind every successful Ph.D. student, there is a loving family". I could not possibly thank you enough for your love.

Jinxi Yang
June 2021, Göteborg

[1] HAPPI is the name of the model we developed for this study.

Table of Contents

Abstract i
List of appended papers iii
Acknowledgements iv
1. Introduction 1
    1.1. Transition to a low-carbon electricity system 1
    1.2. Aim and scope of study 2
    1.3. Thesis structure 2
2. Background 3
    2.1. Modelling approach 3
        2.1.1. Why use a computational model? 3
        2.1.2. Agent-based model: strengths and limitations 3
        2.1.3. Previous studies 5
    2.2. Mitigation strategy: market-based solutions 6
3. Method - The HAPPI Model 7
    3.1. Agent characteristics 7
    3.2. Agent decisions 7
4. Summary of Paper I: Modelling the transition towards a carbon-neutral electricity system - investment decisions and uncertainty 9
    4.1. Transition pathways and competition between low-carbon technologies 10
    4.2. Agents invest heterogeneously 12
    4.3. Value of wind 13
5. Model development 15
6. Summary of Paper II: Financing the transition of the electricity system – an agent-based approach to modelling investment decisions 19
    6.1. Impact of the financial module 20
    6.2. Financial constraints and access to capital 24
    6.3. Agent’s performance 25
7. Conclusions and Discussions 27
    7.1. Policy implications 27
    7.2. Development of models methods 28
    7.3. Limitations of this study 28
    7.4. Key research questions moving forward 29
References 31
Appendix - detailed model description 37
Appended Paper I
Appended Paper II

1. Introduction

1.1. Transition to a low-carbon electricity system

Over the past sixty years, the concentration of carbon dioxide (CO_2) has risen steadily, from below 320 ppm in 1960 to above 417 ppm in 2021 (NOAA, 2021), changing the climate system (IPCC, 2014a). The power sector is one of the main contributors to CO_2 emissions, accounting for about 40%[2] of global CO_2 emissions from fuel combustion, largely due to the combustion of fossil fuels (IEA, 2021; IPCC, 2014b).

Despite being a major source of emissions in its current state, the power sector also has the potential to reduce emissions cost effectively. In their Nationally Determined Contributions (NDC) submitted to the United Nations Framework Convention on Climate Change (UNFCCC), many countries identify increasing the share of renewable power generation as a key strategy to ensure achieving their emission reduction goals (IRENA, 2019). Some countries are even targeting 100% renewable electricity generation (Zhai et al., 2018).

The global banking sector and major investment corporations are also shifting investments towards financing green projects (Partridge, 2020; Quinson and Benhamou, 2021).

The world's energy system is transforming rapidly with the steadily increasing renewable capacity. The global renewable power capacity has grown by an average of 8.6% per year between 2015 and 2018 (IRENA, 2019). In the European Union (EU), the electricity output from wind and solar has already surpassed the output from coal (Fig. 1).

Despite investments in renewable energy increasing steadily (IRENA, 2020b; IRENA and CPI, 2020), global energy-related CO_2 emissions continue to rise as a result of greater energy use (IEA, 2019).

To meet the climate objective and to mitigate the negative impacts of climate change on ecosystems, human health, and well-being, it is crucial for the power sector to reduce emissions and transit to a low-carbon economy. The International Renewable Energy Agency (IRENA) has estimated that the amount of annual investment in renewables must at least be doubled in the 2016-2050 period compared to current values (IRENA, 2020a, b).

Translating this overall objective into concrete measures requires an improved understanding of a complex system consisting of decision-making entities with different characteristics. Increasing our understanding of how imperfect information and heterogeneous agents and financing affect energy system investments would offer a basis for designing more effective policies for the energy transition.

[2]Here, emissions are the sum of emissions from electricity production, combined heat and power plants and heat plants. (IEA, 2020)

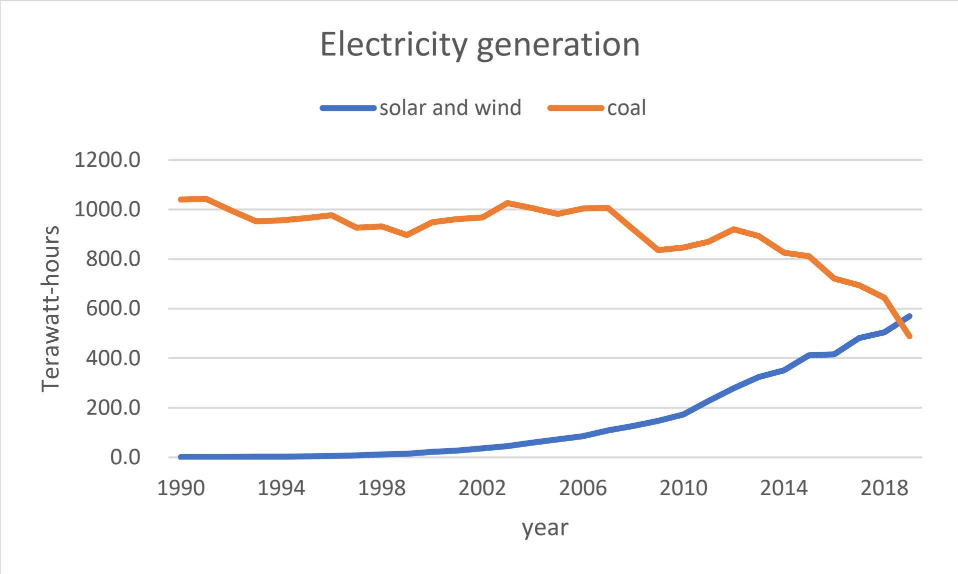


Figure 1. Electricity generation from solar and wind compared to coal in the EU. (Data source: BP (2020))

1.2. Aim and scope of study

The overall aim of this study is to explore the transition to a low-carbon electricity system in a scenario with an increasing carbon tax. We develop and use an agent-based model (ABM) to analyse the transition with a focus on modelling power companies' investment decisions in new power generation capacity, and how these investments impact the development of the overall system over time. We also investigate the competition among low-carbon technologies, the value of wind, and the financial performance of individual power companies, known as *agents* in the model.

The two papers appended have primarily investigated how four factors—the hurdle rate (the minimum rate of return required on an investment), the expectation of the future carbon tax, the availability of capital, and stochasticity (in terms of fuel prices and electricity demand)—impact each agent's investment choices and, in turn, impact the overall transition to a low-carbon electricity system.

This study has also explored the following questions:

- How do investments differ between agents with different characteristics (the hurdle rate and the expectation of the future carbon tax)?
- Do agents with certain characteristics perform better/worse than others?
- How do an agent's prior investments impact its subsequent investment abilities?

1.3. Thesis structure

The remaining part of this licentiate thesis is structured as follows. Section 2 gives the background to the agent-based modelling approach and describes the market-based mitigation strategy. Section 3 introduces *HAPPI* (Heterogeneous Agent-based Power Plant Investment model), the model used for this study. Section 4, 5 and 6 present summaries of Paper I, the model development and Paper II, respectively. Section 7 concludes and discusses implications, limitations of this work, and future research plans.

2. Background

Section 2.1 below discusses why to use computational models to study the energy transition and discusses the pros and cons of the agent-based model approach. Section 2.2 reviews previous studies that have used ABMs to study the energy transition.

This section also gives a brief overview of the market-based policy instrument for CO_2 mitigation. Section 2.3 discusses two market-based measures for CO_2 mitigation—cap-and-trade and a carbon tax.

2.1. Modelling approach

2.1.1. Why use a computational model?

The energy transition is a complex transformation process shaped by economic development, technological innovation, policy change, and other factors (Cherp et al., 2018). Models can help us comprehend this complexity by quantifying the impacts of potential pathways, analysing interactions among actors, testing different scenarios, and more. (Desouza and Lin, 2011; Gilbert et al., 2018; Government Office for Science, 2018; Horschig and Thrän, 2017)

Models can also provide cost-benefit analyses of various policy options and help manage risk and uncertainty (Calder et al., 2018). For instance, epidemic models have been employed worldwide to understand and forecast the spread COVID-19 virus (cf. Government of Canada (2021); the Australian Government (2020); the UK Government (2021)). These models have informed policymakers and assisted governments in formulating control strategies.

Computational models serve as tools that support decision-making. Studies in psychology and behavioural economics show that human decisions are often biased and illogical (Kahneman, 2011; Thaler and Sunstein, 2008). Models can guide strategies to make better decisions and enhance the quality of policy design, especially when dealing with complex and unfamiliar problems such as an energy system transition.

2.1.2. Agent-based model: strengths and limitations

In the energy system study, commonly used model types include optimisation models, equilibrium models, and simulation models. Here, we use the agent-based model (ABM), which is a simulation model.

An ABM is typically composed of individual agents, an environment, and a description of agent-agent and agent-environment interactions (Wilensky and Rand, 2015). An agent is an autonomous decision-making element with properties and actions. An agent can be a human or non-human object such as a virus, bird, or government. Each agent individually assesses their situation and makes decisions based on a set of rules (Bonabeau, 2002). The environment is the landscape on which agents interact. An ABM simulates the agents' actions and agent-environment interactions.

An ABM has advantages and disadvantages relative to other models (Arthur, 2021; Bonabeau, 2002; Eberlen et al., 2017; Galan et al., 2009; Laubenbacher et al., 2013; Loomis et al., 2008; Manzo, 2014). Advantages include:

- explicitly models individual decision-making entities and their interactions, and allows for incorporating non-monetary influences on agents' decisions;

- including heterogeneous agents, including various forms of limited information, is straightforward;
- good for including agent interactions and adaptations;
- allows for more realistic modelling by providing a natural and explicit description of a system and its mechanisms; and
- has the potential to mimic the synergistic effects of interactions that give rise to emergent system properties.

However, an ABM approach also has disadvantages, including:

- the model can be very complex so that understanding the results in reasonable detail is not straightforward;
- selecting the appropriate number of features and behaviours to include in the model can be challenging
- quantifying, calibrating, and justifying features such as irrational behaviour, subjective choices, and complex psychology is difficult.

The idea of agent-based modelling appeared in physics in the 1930s (Gooding, 2019); one of the earliest ABMs was Schelling's segregation model (Schelling, 1971). ABM has emerged as an important tool for various research fields, such as social science, biology, economics, public health, logistics. In the field of the energy transition, the application of ABM also has been growing (Bale et al., 2015; Hansen et al., 2019; Klein et al., 2019; Ma and Nakamori, 2009).

The existing mainstream modelling tools are limited in their ability to include features such as heterogeneous characteristics of decision-makers, bounded-rationality, historic path-dependency of the energy system, imitation and interaction among market players. But all these features can be captured in ABMs in a reasonably simple way, which is part of the reason behind their increased use.

ABMs can also represent the essential characteristics of the energy transition. Köhler et al. (2018) argue that to address essential features of sustainability transitions, a model needs to represent six characteristics of the transition: non-linear behaviour, changes in the functions of elements, changes in social values and norms, diversity and heterogeneity, dynamics at and across different scales (feedbacks between the micro and macro levels), and responses to unpredictable events (uncertainties).

The need for agent-based approaches in studying the energy systems transition is highlighted and demonstrated in recent publications. The next section provides examples.

2.1.3. Previous studies

The ABM approach has increasingly been applied to studying the energy transition. Several recently published studies have demonstrated the strength of the ABM and provided additional insights not captured by other types of models.

For example, the EMLab-Generation (Energy Modelling Laboratory) model (Chappin et al., 2017) simulates power companies' investments in generation capacity under energy and climate policies. The agents in the model are heterogeneous, have imperfect expectations, and make investment decisions outside of ideal conditions. Among other things, the model has been used to analyse two ways of reforming the European Union Emission Trading Scheme (Chappin et al., 2017).

ENGAGE (an evolutionary economic model of climate policy and negotiation) (Gerst et al., 2013) is another example. The model simulates the dynamic interaction among international climate treaty negotiations, national policy formation, and domestic economic and technological systems. Agents in the model are negotiators, firms, and consumers. The agents observe and interact with their surrounding environment and other agents. The agents have limited cognitive abilities and heterogeneous beliefs and vulnerabilities to climate change.

A further example is the BLUE (Behaviour, Lifestyles and Uncertainty Energy) model (Li, 2017; Li and Strachan, 2019). It models the energy system transitions in the UK and the associated changes to technologies, energy use, and emissions. It simulates the individual behaviours of multiple energy system actors who interact dynamically in the form of changes to technologies, demands, and prices. Actors in the model are heterogeneous in several characteristics, such as their demand elasticities, the propensity to cost-optimise, perception of non-monetary costs, hurdle rates, and investment cycle years.

Kraan et al. (2018) study energy transition pathways by simulating decision-making for investments in new power plants. The results show that under various carbon-price scenarios, the existence of heterogeneous agents results in a wide spectrum of possible transition pathways. Jonson et al. (2020) investigate the competition between variable renewable-power sources and a carbon-neutral backstop technology under a gradually increasing carbon tax scenario.

Barazza and Strachan (2020) use the BRAIN-Energy (Bounded Rationality Agents Investment model) and explore the impacts of agent heterogeneity on investment decisions about power generation technologies, comparing the UK, Germany, and Italy. The agents in the model are incumbent utilities, independent power producers, new-entrants, municipal utilities, institutional investors, and households. Heterogeneity is represented by several characteristics, such as the aim of investment, technology preferences, foresight length, capital costs for investment, etc.

2.2. Mitigation strategy: market-based solutions

When considering actions to reduce GHG emissions, policymakers have various options. Market-based approaches, such as a cap-and-trade system for GHG emissions or a carbon tax, have been implemented widely (the World Bank, 2021).

Under a carbon tax, the government sets a price that emitters must pay for each GHG unit they emit. So far, 35 national-level or subnational-level carbon tax instruments have been implemented, for example in Finland, Sweden, UK, etc. (the World Bank, 2021).

Under a cap-and-trade approach, the government sets the total emissions (the cap), emission allowances equalling the cap are distributed (either freely or through auction) to emitters, and the market determines a carbon price. The best-known cap-and-trade system is perhaps the European Union Emissions Trading System (EU ETS) (European Commission, 2015). After experiencing a period with a relatively low price in 2018 and 2019, the carbon price in the EU ETS has risen to above 50€ per ton CO_2 recently in 2021 (Fig. 2).

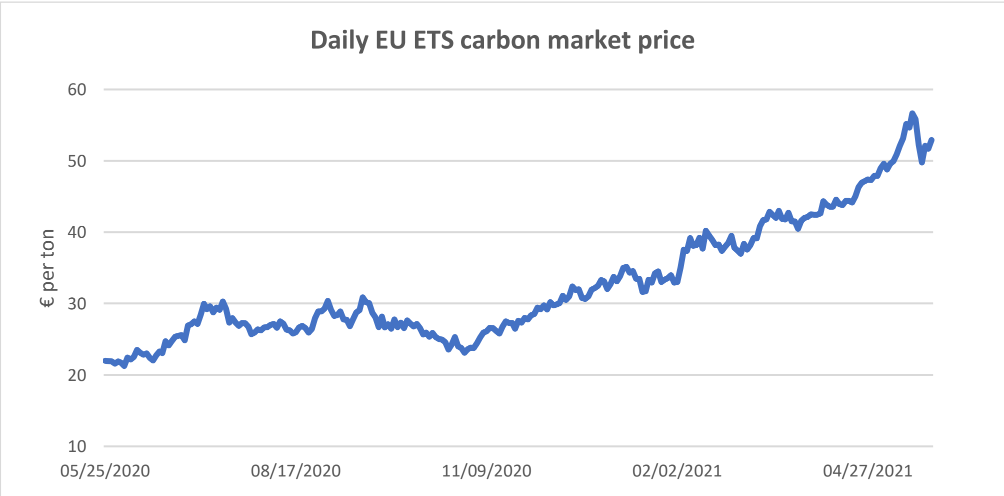


Figure 2 European Union Emissions Trading System carbon market price (data Source: Ember, https://ember-climate.org/data/carbon-price-viewer/)

While some favour a cap-and-trade system, others support a carbon tax (Goulder and Schein, 2013). Those who support the cap-and-trade system argue that it provides certainty about the size of emissions reductions.

Those who favour a carbon tax argue that it is more transparent and that the carbon price will be less volatile. The tax does not require new markets. However, a carbon tax does not offer the same degree of emissions certainty as cap-and-trade.

In our model, we implement a carbon price that reflects a carbon tax paid by power companies.

3. Method - The HAPPI Model

We have developed *HAPPI*, the Heterogeneous Agent-based Power Plant Investment model to explore the transition of the electricity system towards a low-carbon future. We focus on agents' investment choices and model the transition as occurring through the installation of new power plants and the exit of old plants as they are retired.

3.1. Agent characteristics

The agents in our model are heterogeneous power companies, and their heterogeneity is represented by two attributes. The first attribute is the investment risk perceived by each agent, represented by the hurdle rate, r, the agent uses.

The second attribute is the carbon price an agent expects. Agents have limited information about future carbon prices. They know the true carbon tax of next year, and they estimate the tax level n years ahead. The carbon price an agent expects, $F_b(t+n)$, is given by the true tax in the next year $T(t+1)$ plus a factor b times the difference between the true tax $T(t+n)$ in n years time and $T(t+1)$:

$$F_b(t+n) = T(t+1) + b\big(T(t+n) - T(t+1)\big) \qquad (1)$$

Different agents use different values for b, which means they expect different growth rates of the carbon price. The agents assume that the tax after n years stays at the same level as $F_b(t+n)$.

3.2. Agent decisions

The agents make two types of decisions. They decide on investments—whether to invest and if so in what technology—and on whether to operate their plants to generate power. They aim to maximise their own profit.

Investments

Each year, plants that reach the end of their lifespan are decommissioned, and agents take turns making investment decisions for new power plants. (The order in which they get to decide is randomised.) To invest, an agent can choose from six types of power plants, namely, coal-fired, gas-fired, gas-fired with carbon capture and storage (gasCCS), nuclear, photovoltaic (PV), and wind. The parameter settings for the plants are listed in Table A3 in the Appendix.

The decision is based on the expected profitability of the potential investment. Each agent evaluates each of the six investment options and chooses the plant with the highest expected profits to invest in. The profit is measured by the profitability index

$$profitability\ index = \frac{NPV}{I} \times CRF \qquad (2)$$

$$NPV = \sum_{t=1}^{T} \frac{R_t - C_t}{(1+r)^t} - I \qquad (3)$$

$$CRF = \frac{r}{1-(1+r)^{-T}} \qquad (4)$$

Here NPV is the net present value of the net revenue during a plant's lifespan T. R_t and C_t are the revenues and operational costs in year t, respectively. The revenue is from electricity sold, see the revenue calculation in the next section. I is the plant's investment cost, and r is the hurdle rate employed by the individual agent. The capital recovery factor, CRF, a ratio used to calculate the present value of a series of equal annual cash flows, takes into account the different lifespans of different types of plants.

If an agent decides to invest, the agent needs to find means to finance the investment. In Paper I, we assume that agents can borrow all the money from the bank as a loan, and they repay the loan with a mortgage (equal to the annuitized cost of the investment cost of a plant). In Paper II, we add a financial module: Agents are required to provide a certain fraction of the investment cost from their own capital, and the rest can be borrowed as loans. This means that agents that have performed poorly may not be able to make new investments. Hence, the availability of capital can become a constraint on the expansion of new technologies. (Details of the financial module are presented in Section 5.)

Once an investment is made, the decision is immediately made public, so subsequent decision makers take previous investment decisions into account. The newly invested plant starts operating the next year.

Power generation

The agents produce electricity in an ideal electricity market. There is no strategic generation behaviour. Agents produce electricity so long as the electricity price is greater than (or equal to) the running cost of their plants, following the merit order.

To characterise the variation of electricity demand and the availability of variable renewable supply from wind and solar, each year is divided into 64 time slices in the model. For each time slice τ, the electricity price p_τ and the production quantity q_τ are determined by an iso-elastic demand-supply function

$$q_\tau = q_{0,\tau} \times \left(\frac{p_\tau}{p_0}\right)^{\epsilon} \tag{5}$$

Electricity price p_τ is reached when the electricity produced (and consumed) q_τ meets the demand. The reference demand $q_{0,\tau}$ is given and reflects the varying demand over different time slices in Germany in 2011. The reference electricity price $p_0 = 3.25\text{€ct/kWh}$ is the price at which production meets the reference demand, with elasticity $\varepsilon = -0.05$ (Jonson et al., 2020).

Detailed information on time slices, reference demand, and prices are listed in Table A2 in the Appendix. The Appendix also includes a more detailed model description.

4. Summary of Paper I: Modelling the transition towards a carbon-neutral electricity system - investment decisions and uncertainty

This section summarises the research questions, methods, and main findings of Paper I.

To better understand energy technology investment decisions and how they impact the power system and the pace of mitigation, we develop and employ the HAPPI model to analyse the transition toward a carbon neutral electricity system.

We mainly explore the impact of the heterogeneous agent characteristics (represented by hurdle rates and expectations for the future carbon tax) on the agents' decisions. The main questions investigated in Paper I are:

- How does the hurdle rate affect agents' investment decisions, and how does that in turn impact the overall system dynamics?
- How do different expectations for the future carbon tax affect agents' investment decisions?
- How does the heterogeneity of the agents affect electricity prices, output variability, and the reduction rate of carbon emissions?
- Does the value of wind drop as a function of the installed capacity of wind (the so called "cannibalisation effect")?

To answer these questions, we design three different cases. In one case, agents are homogeneous; they use the same hurdle rate and expect the same future carbon price. We also design two heterogeneous agent cases, where agents either use different hurdle rates or expect different carbon prices.

In the homogeneous agent case, all agents use hurdle rate $r = 8\%/yr$, and $b = 1$ and with one-year foresight $n = 1$. (See Eq. 1).

In the first heterogeneous agent case, 25 agents use hurdle rate values in the range from 5%/yr to 11%/yr (with a step of 0.25%), $r = [5\%, 5.25\%, 5{,}5\%, \dots, 10.75\%, 11\%]$. The average value of the hurdle rates is 8%/yr. All agents have $b = 1$ with one-year foresight $n = 1$. This is the HHR (heterogeneous hurdle rate) case.

In the second heterogeneous case, 16 agents expect different growth rates b for the carbon tax. The value of b ranges uniformly from 0 to 1.5 (with a step of 0.1). They know the true carbon tax for next year, and they estimate the tax level ten years ahead ($n = 10$). This means that agents that use a value for b that is less than 1 underestimate the growth of the tax, while agents using $b = 1$ expect the true tax in ten years, and agents that use b greater than 1 overestimate the tax. All agents use the same hurdle rate $r = 8\%/yr$. This is the HF (heterogeneous foresight) case.

The model starts with a stationary state with 64 GW coal and 2 GW gas. The CO_2 tax stays at 0 for the first ten years and then grows linearly by 2.5€/ton per year to 100 €/ton at year 50, and stays at 100 €/ton per ton thereafter.

This study focuses on evaluating the impact of heterogeneous values for the hurdle rates (r) and the expectation of future carbon price (b) individually. We compare the results from the heterogeneous cases with the homogeneous case.

The next section first presents the results on the system level from all three cases, which illustrate how the overall capacity mix and the emissions change over time, then presents the individual agents' installed capacity, and, lastly, presents the value of the wind.

4.1. Transition pathways and competition between low-carbon technologies

Figures 3 and 4 show that under a growing tax scenario, the transition from a fossil-based system to a low-carbon system occurs earlier in the heterogeneous cases. Investments in low-carbon technologies start earlier in the heterogeneous cases. The HHR case includes agents that use a low hurdle rate (i.e., $r = 5\%/yr$, compared to 8% in the homogeneous case). With a lower hurdle rate, the levelised costs of both nuclear and wind drop more than for coal (Fig. 5), so wind and nuclear are introduced earlier than in the homogeneous case.

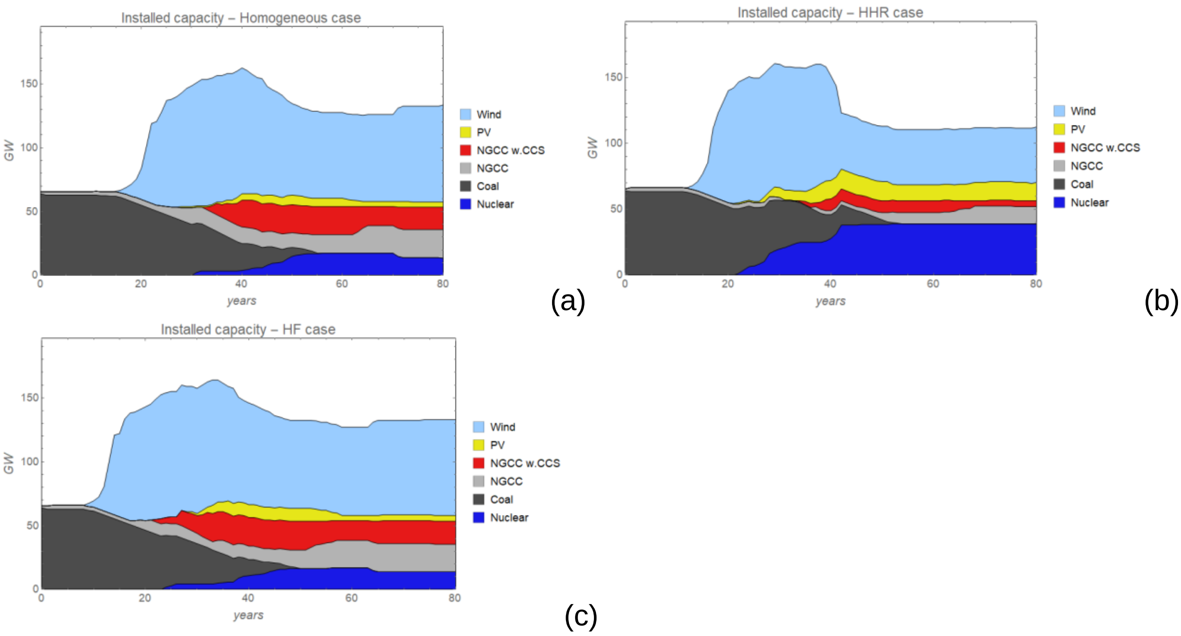


Figure 3 The system installed capacity over 80 years in the (a) homogeneous case, (b) HHR case, and (c) HF case. Starting with only coal and gas, the system gradually transitions to a low-carbon system in all three cases. Wind is the first low-carbon technology that expands, followed by nuclear, gas with CCS, and solar PV. Investments in low-carbon technologies start earlier in the heterogeneous cases than in the homogeneous case.

In the HF case, agents have ten-year foresight and several agents expect the carbon tax to increase faster than in the homogeneous case, therefore they start to invest in low-carbon technologies earlier. Due to the early adoption of low-carbon technology in the HHR and HF cases, emissions drop earlier than in the homogeneous case, see Figure 4.

One difference between the two heterogeneous cases is that in the HHR case there is noticeably more nuclear and less wind than in the HF case in the end. This is because the lower hurdle rate lowers the levelised cost of nuclear more than for gas-fired plants (both with and without CCS), and since wind and gas-fired power plants are two complementary technologies (Jonson et al., 2020; Sepulveda et al., 2018), wind capacity drops due to the decline of gas-fired power plants.

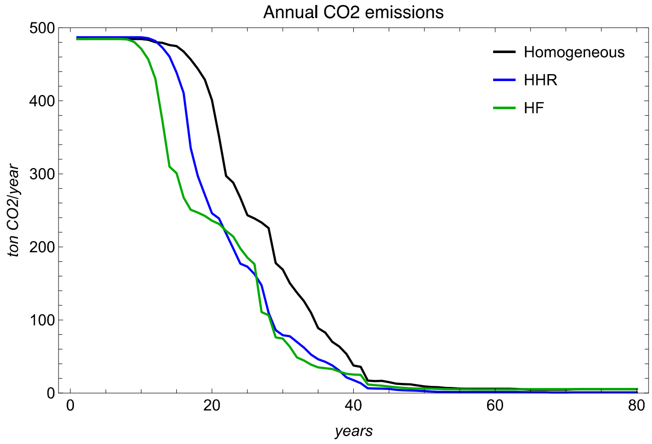


Figure 4 Emission trajectories in the homogeneous case, the HHR case, and the HF case. Emissions in all three cases drop to almost zero around year 50, but in the HHR and HF cases, the emissions drop earlier than in the homogeneous case due to the earlier adoption of low-carbon technologies.

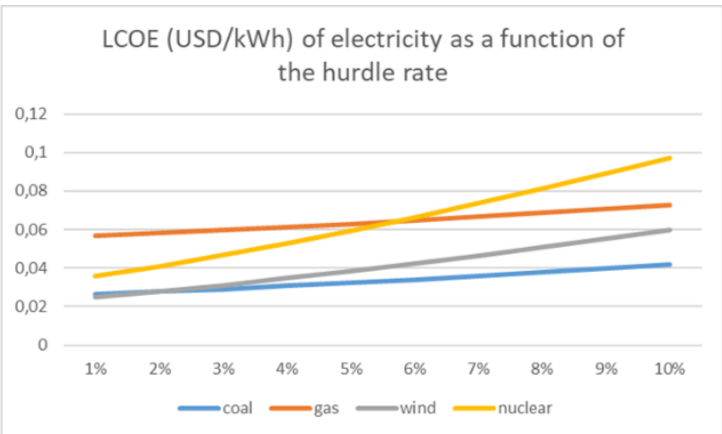


Figure 5 The levelised cost of electricity (LCOE) drops with the hurdle rate. The decline rate varies among different technologies.

4.2. Agents invest heterogeneously

In the two cases with heterogeneous agents, the overall investment is dominated by a single agent (see Figures 6 and 7). In the HHR case, the agent with the lowest hurdle rate invests the most. With a lower hurdle rate, an agent is more willing to invest. The investments lower the electricity price, which further lowers the profitability for agents with higher hurdle rates requiring a higher return.

In the HF case, the agent that expects the highest carbon tax price dominates investing (but only before the stabilisation of the carbon price). By expecting a higher carbon price, this agent foresees a higher electricity price than other agents and is therefore more willing to invest. However, after the carbon price has stabilised (year 60), all agents foresee the same future carbon price, and investments are evenly distributed after that.

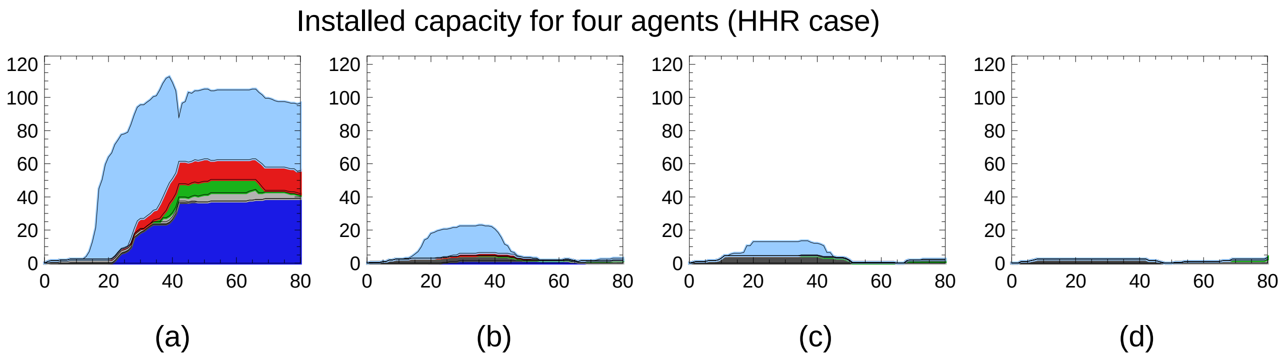


Figure 6 Illustration of the installed capacity for some agents in the HHR case, (a) r=5.0%, (b) r=5.25%, (c) r=5.5%, (d) r=5.75%. The agent with r= 5% dominates the investing, while agents with r>6.75% make no investments.

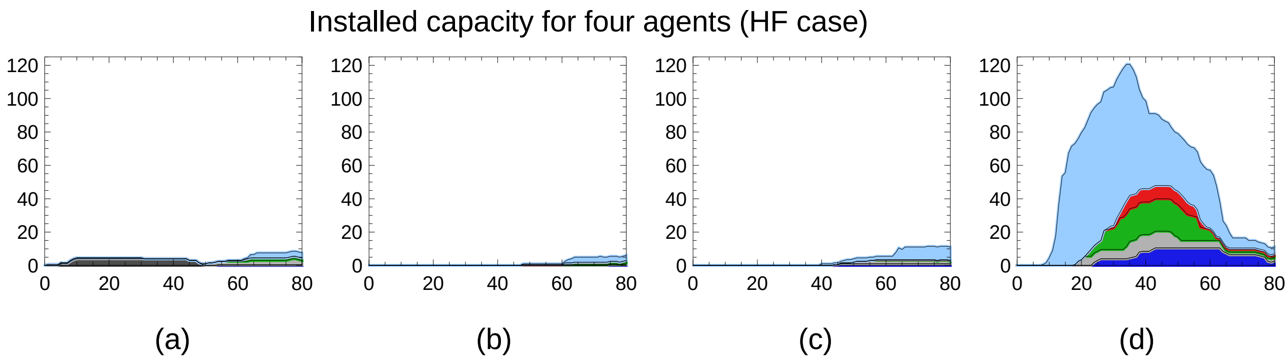


Figure 7 Illustration of the installed capacity for some agents in the HF case, (a) β =0.0, (b) β =1.0, (c) β =1.2, (d) β =1.5. (β is the multiplication factor of expectation of CO_2 tax). The agent with β =1.5 dominates the investing for the first 50 years; afterwards, all agents contribute to investing in new capacity.

4.3. Value of wind

Since wind technology has a zero running cost, adding wind to the power system puts a downward pressure on the price. Studies show that the penetration of wind (and solar) undermines its own value—a phenomenon known as the "cannibalisation effect" (Hirth, 2013; López Prol et al., 2020) .

Our study finds that when wind is introduced as a result of an increasing carbon tax, the average revenue per kWh achieved by wind generators (the value of wind) will not drop in absolute terms but in relative terms (Fig. 8). Our result confirms the findings by (Brown and Reichenberg, 2021). The reason the absolute value of wind does not drop is that in a competitive market, agents will not invest in wind if the average revenue received per kWh is lower than the levelised cost of wind. The reason why the relative value (the wind value factor) tends to drop is that once investments in wind are made, this puts downward pressure on electricity prices when wind output is high.

However, if wind is introduced through, for instance, an investment subsidy, its value tends to drop with installed capacity (Brown and Reichenberg, 2021; Hirth, 2013).

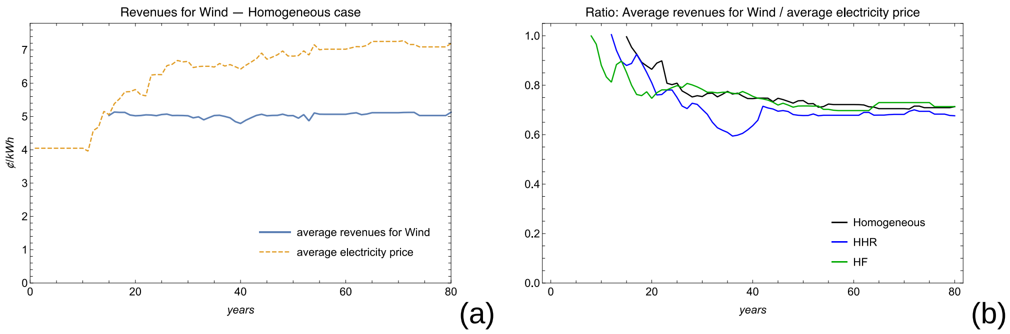


Figure 8 The value of wind. (a) the absolute average revenue per kWh does not drop for wind generators; (b) relative value of wind drops.

5. Model development

After Paper I, we made a major extension of the model by including a financial module. This module keeps track of each agent's financial status, such as equity, debt, and the money in its bank account.

The financial module includes the following mechanisms:

- First, an agent is assumed to use its own savings to pay for a certain fraction (denoted by f) of a new investment, while the remaining part of the investment, $(1 - f)$, is borrowed from the bank with interest.
- Second, an agent can accumulate money in its own bank account by selling electricity (from its plant operations).
- Third, a certain fraction of the capital can be paid to the shareholders as a dividend, provided that the planned investments for the coming years can be made.
- If an agent's equity goes below 0, it goes bankrupt and is not allowed to make further investments.

This financial module not only tracks each agent's financial status, but also functions as a (financial) feedback loop to the model (Fig. 9), which means that an agent's previous investment will positively or negatively impact its ability to invest later, depending on the profitability of previous investments, and this will also impact the overall system's transition.

Integrated assessment models (IAMs) typically assume that companies have access to capital at no cost, and these models do not take into account different levels of risk aversion among investors; because this could distort assessments of the costs and benefits of climate mitigation policies, a recent study argues that IAMs should take into account the feedback loop between the financial system and mitigation pathways to better inform policy and investment decisions (Battiston et al., 2021).

Our financial module can be seen as a first step to connect the financial system and the mitigation scenario circularly in the model. Please see the Appendix for a more detailed description of both the financial module and the model as a whole.

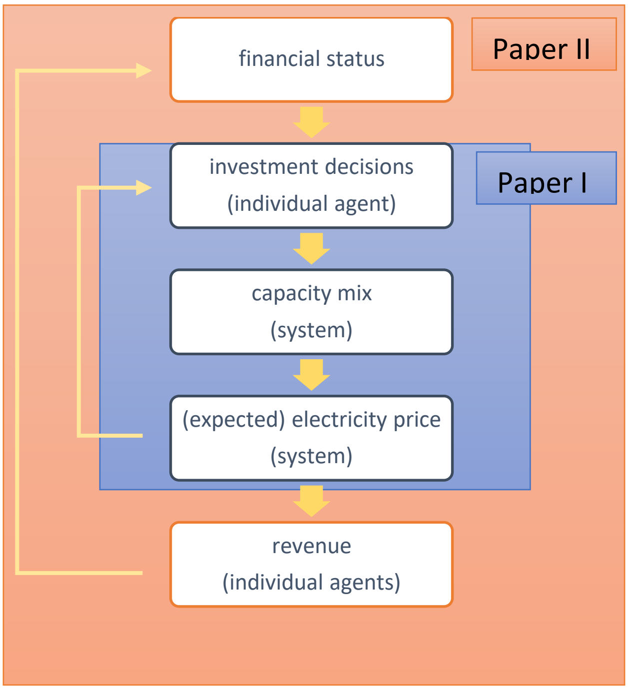


Figure 9. The feedback loop in the HAPPI model. (In Paper II, we extend the feedback loop by adding a financial component at the beginning and another at the end of the loop. To invest, an agent first needs to determine if it has enough capital. At the end of the loop, the electricity price impacts the agent's revenue, which will then enhance or reduce the agent's financial status in the next investment round.

In addition to the new financial module, we enable the model to implement stochastic events, such as a stochastic fuel price and stochastic electricity demand. Also, now agents can be heterogeneous in both the hurdle rate r and their expectations about the future carbon price b, simultaneously. Table 1 below provides an overview of the model development between Paper I and Paper II, and it also shows how cases in Paper II build on cases in Paper I.

Table 1 Compare the case designs in Paper I and Paper II. In Paper I, agents are only heterogeneous in either r (hurdle rate) or b (expectation of carbon price); in Paper II, agents are heterogeneous in both r and b. In Paper II, a financial module and stochasticity are also added to the analysis.

	Case	Heterogeneous hurdle rates *r*	Heterogeneous expectations *b*	Foresight (years)	Financial module	Stochasticity
Paper I	1: Homogeneous			1		
	2: Heterogeneous hurdle rate (HHR)	X		1		
	3: Heterogeneous foresight (HF)		X	10		
Paper II	4: Varying fraction, f, of new investment from own savings	X	X	10	X	
	5: Varying initial capital, i	X	X	10	X	
	6: Stochasticity	X	X	10	X	X

6. Summary of Paper II: Financing the transition of the electricity system – an agent-based approach to modelling investment decisions

This section summarises the research questions, methods, and main findings of Paper II. The paper mainly investigates the following questions:

- How do different levels of financial constraints and the access to capital impact the agents' investment decisions and their economic performance, and how does this, in turn, impact the transition of the electricity system?
- Which investment strategy more robustly secures good economic performance, thus reducing the risk for bankruptcy while guaranteeing a certain level of profitability when investing under uncertainty?

In Paper II, we primarily investigate three cases (Cases 4-6 in Table 1). We test four variables,

1) f : the fraction of an investment that is financed by an agent's own capital,
2) i : the initial capital (M€) in an agent's bank account,
3) fuel prices, and
4) electricity demand.

The financial constraints and access to capital are represented by the f and i values. A lower f value means that agents will have lower requirements for borrowing money from the bank, and a higher i value gives agents more (initial) available capital in their bank account.

In Case 4, we test six values of f, the fraction of an investment that has to come from the agent's own capital; $f \in \{0\%, 10\%, 20\%, 30\%, 40\%, 50\%\}$. The initial capital i is set at a reference level; $i = 400$ M€, and there is no stochasticity in fuel price or electricity demand.

In Case 5, we test five levels of the initial capital i, which ranges in the set of [225, 400, 900, 1200, 2000] M€. (The fraction f is set at its reference level ($f = 30\%$), and there is no stochasticity in fuel price or electricity demand.)

In Case 6, stochastic fossil fuel price (gas and coal) and electricity demand are implemented, (while $f = 30\%, i = 400M€$). We use the autoregressive model to generate the random process. (The autoregressive model is provided in the Appendix.)

We compare all the cases with a base case where while $f = 30\%, i = 400M€$ with no stochasticity in fuel price or electricity demand.

For all three cases investigated in Paper II, we set $r \in \{4.5\%, 5\%, 6\%, 8\%\}$ and $b \in \{0, 0.5, 1.0, 1.5, 2.0\}$. We use all combinations of r and b, so there are 20 active agents in the model.

As in Paper I, the model starts with a stationary state with 64 GW coal and 2 GW gas. The CO_2 tax stays at 0 for the first ten years and then grows linearly by 2€/ton per year to 100 €/ton in year 60 and stays at 100 €/ton thereafter.

The next section presents the main results from Paper II. Before presenting results from Cases 4-6, we first compare results from cases with and without the financial module activated.

6.1. Impact of the financial module

Figures 10-12 show the development of the installed capacity over the course of 80 years in cases with and without the financial module. The left column shows the installed capacity of the overall system, and the right column shows the individual agents' installed capacity.

We observe that while the capacity on the system level displays a similar trend (see Figures 10a, 11a, and 12a), the results on the agent level are very different depending on whether and how the financial module is implemented (see Figures 10b, 11b, and 12b). Without the financial module, a single agent dominates as investor (Figure 10b). The dominant agent is the one that has the lowest hurdle rate (4.5%/yr) while expecting the highest carbon tax (b=2). By requiring a smaller return on investment and expecting higher future electricity prices by overestimating the carbon tax, this agent is more willing to invest. Investments by this agent lower the overall electricity price and crowd out other agents.

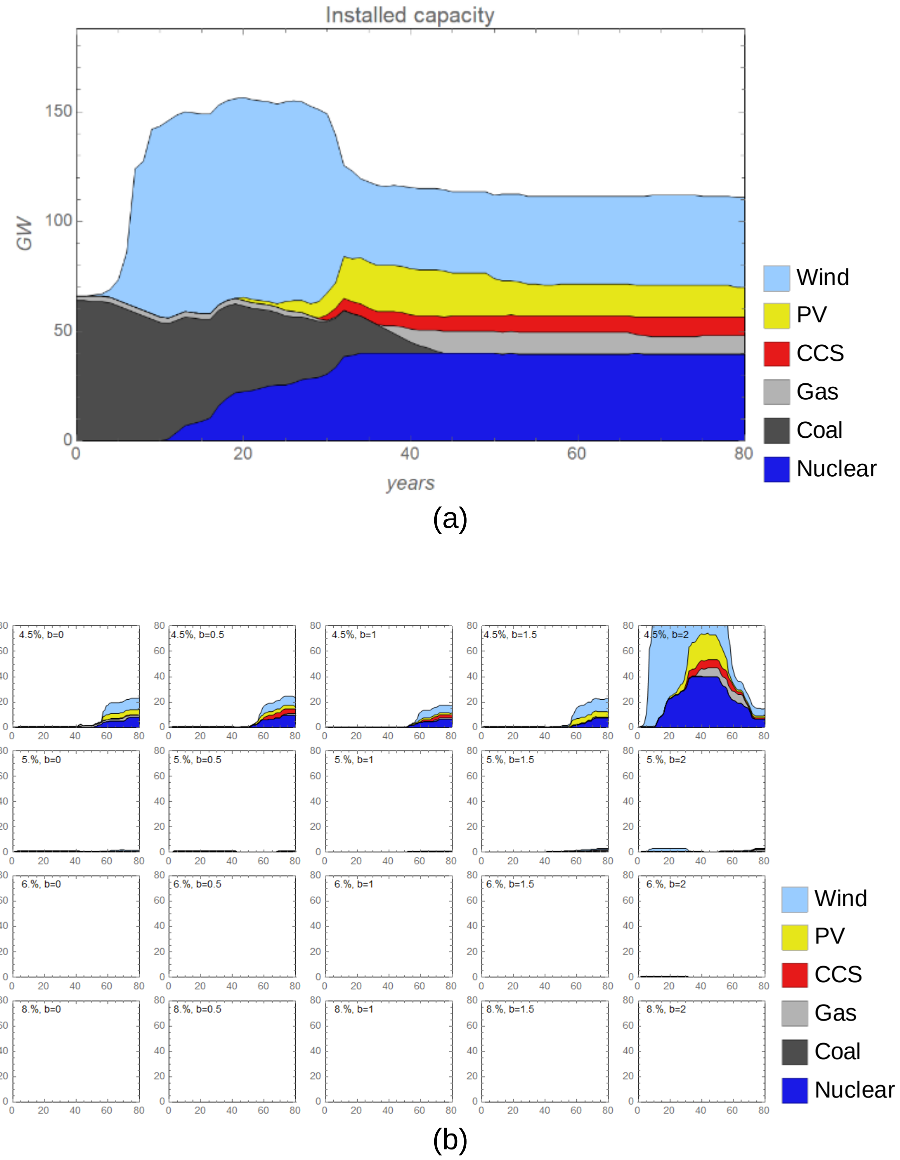


Figure 10 Installed capacity without financial feedback module implemented: Agents do not go bankrupt and can borrow 100% of the investment amount from the bank regardless of their financial situation. (a) Installed system capacity; (b) installed capacity for 20 individual agents. The agent with the lowest hurdle rate and the highest expected carbon price dominates overall investment.

However, when the financial module is implemented, results show that details of the structure of investment financing may strongly affect the results on the agent level.

Comparing Figure 10b (no financial module) and Figure 11b (with the financial module and therefore with the possibility of going bankrupt but with $f = 0\%$), we see that the dominant agent from Figure 10b instead goes bankrupt when this possibility is included as in Figure 11b. This discrepancy illustrates the importance of including a financial module in order for the model to more realistically reflect investment decisions and consequences.

Then, when comparing Figure 11b (with the financial module and $f = 0\%$) with Figure 12b (which shows results for $f = 30\%$), we see that when a higher value of f is assumed, investments are more evenly distributed among agents.

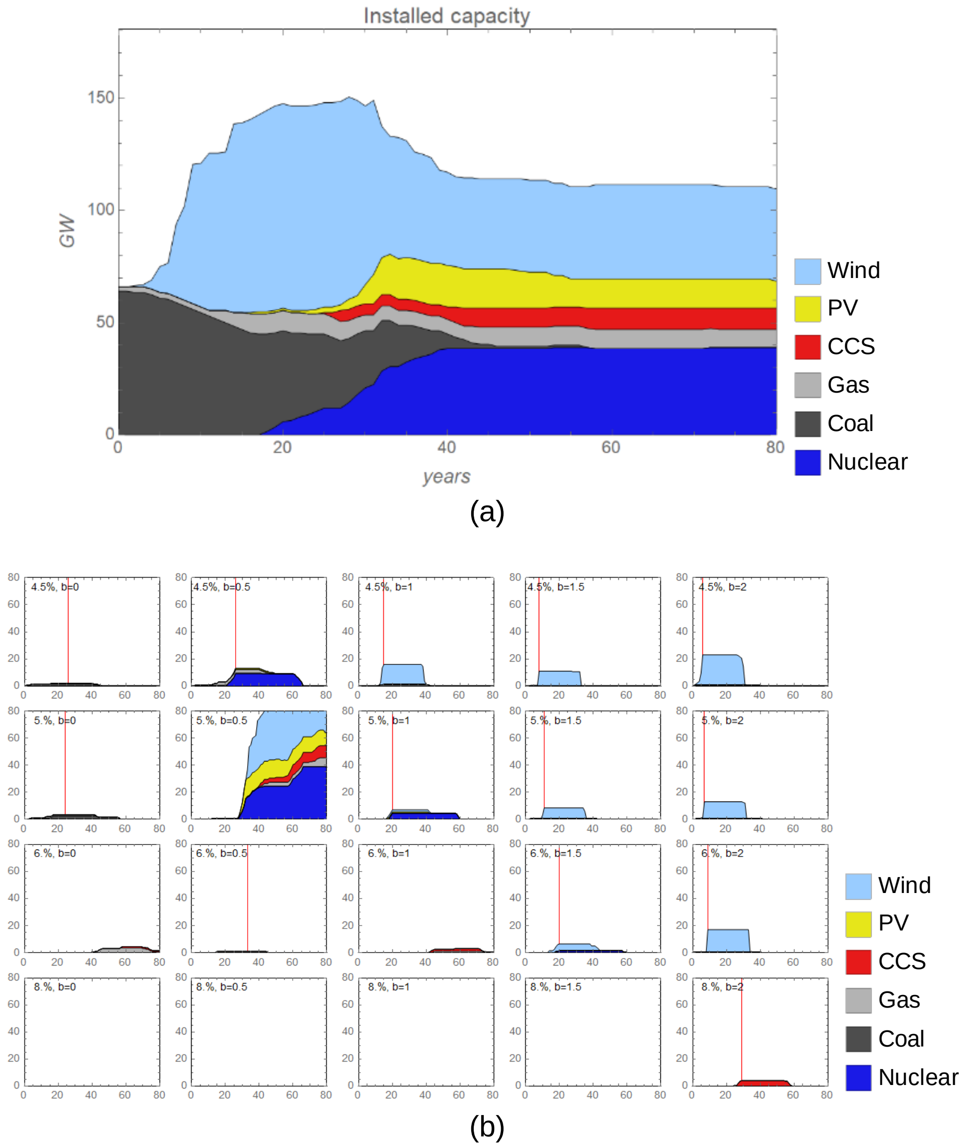
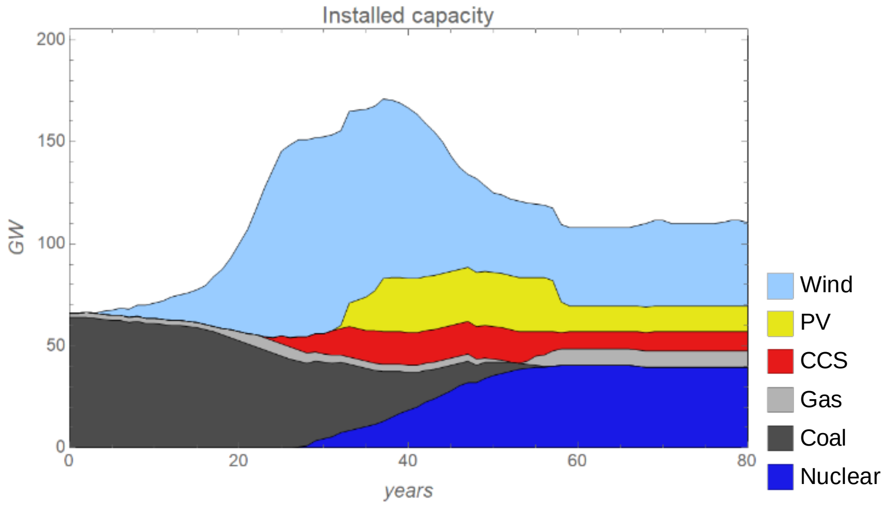
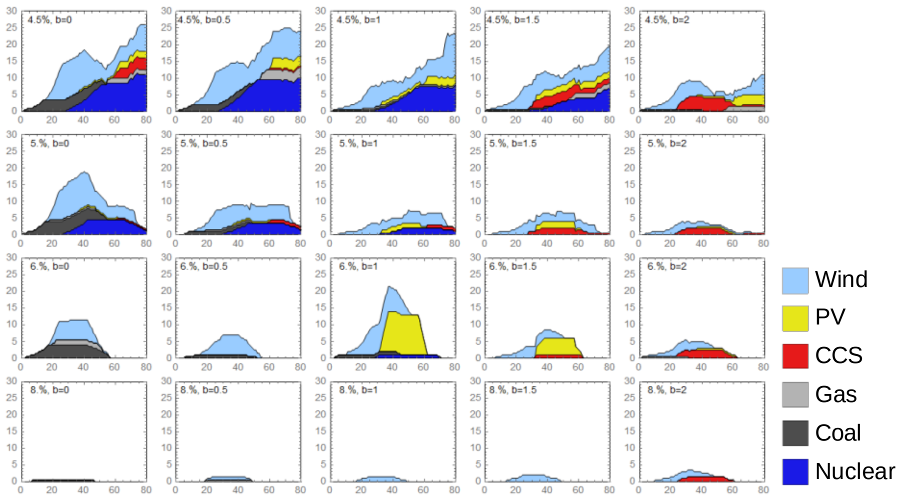


Figure 11 Installed capacity with financial feedback module implemented, f = 0% and i = 400M€. Agents can now go bankrupt. (a) Installed system capacity; (b) installed capacity for 20 individual agents. The vertical red line indicates the year an agent goes bankrupt. The agent with the lowest hurdle rate and the highest expected carbon price goes bankrupt in this case.



(a)



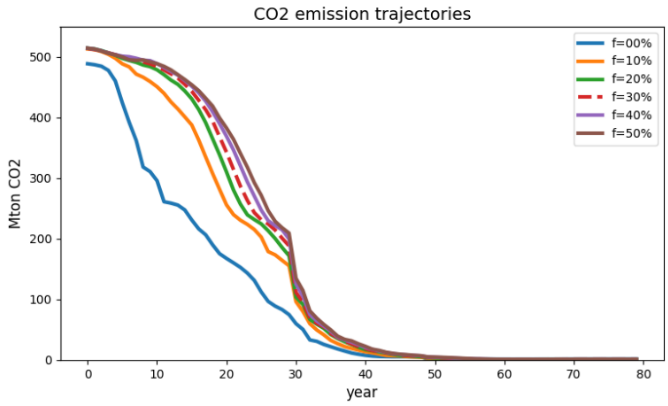
(b)

Figure 12 Installed capacity with financial feedback module implemented, f = 30% and i = 400M€. (a) Installed system capacity; (b) installed capacity for 20 individual agents. With the higher f value compared to in Figure 11, investments are more evenly distributed among agents.

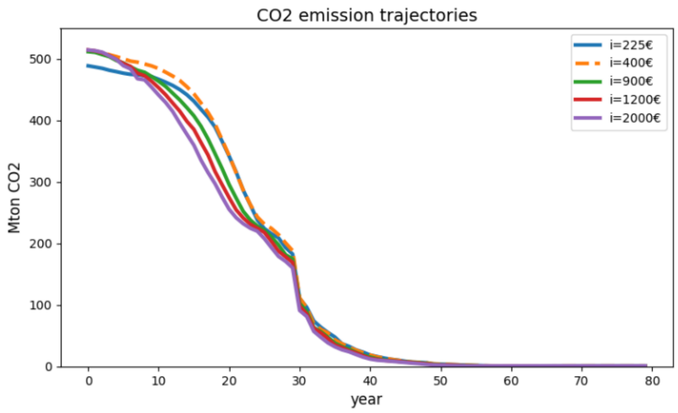
In the next part, we present results from Paper II in which the financial module is implemented with varying assumptions on f and i values.

6.2. Financial constraints and access to capital

We investigate how financial constraints and access to capital affect the pace of the transition to a low-carbon electricity system. Figure 13 shows that with different levels of financial constraints and access to capital (represented by the f and i values), CO_2 emissions are reduced at different rates. The overall trend is that when agents have more access to capital and are less financially constrained, emissions are mitigated more rapidly because agents invest more in capital-intensive low-carbon technologies such as wind, nuclear, and PV.



(a)



(b)

Figure 13 Emission trajectories for (a) different values of f and (b) different values of i. The emissions are mitigated faster when agents have fewer constraints and more access to capital.

6.3. Agent's performance

Overall, the agents that expect the lowest or highest carbon prices, are more likely to go bankrupt (Fig. 14).

The main reason for agents expecting the lowest carbon price to go bankrupt is that they invest in unprofitable coal power plants (see the IRR in Fig. 15). Agents that expect the highest carbon price have a risk of going bankrupt mainly due to their unprofitable investments in gasCCS.

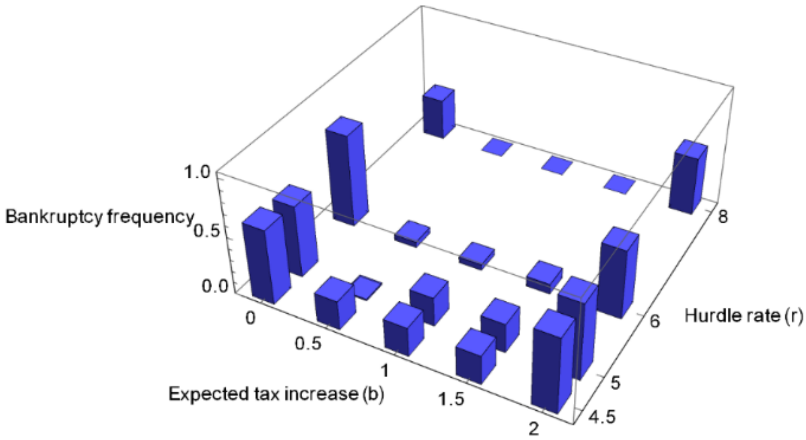


Figure 14 The bankruptcy frequency of 20 individual agents. Agents expecting the lowest or highest carbon prices have a higher risk of bankruptcy. This is an aggregate result of all cases with no stochastic fuel prices or electricity demand.

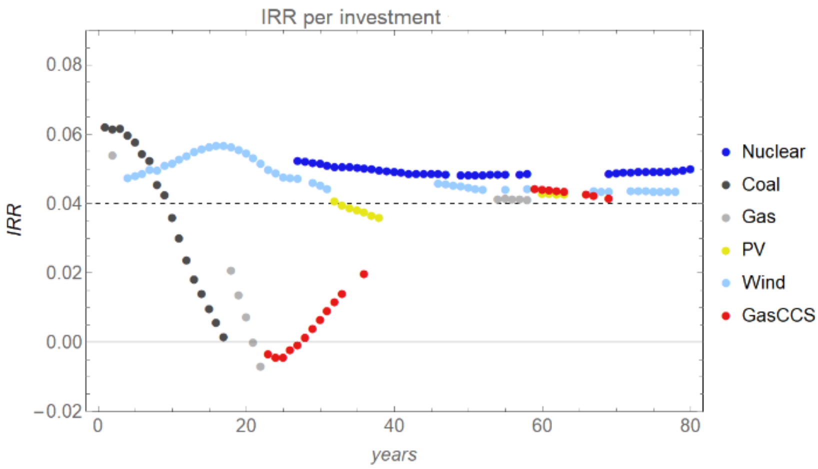


Figure 15 Internal rate of return (IRR) in the base case (f =30% and i= 400M€). Each dot indicates the IRR for an investment made in a particular year.

Moreover, each agent’s financial performance is also evaluated by the investment return on equity (ROE). Figure 16 illustrates the development of equity over 80 years, and it shows that agents expecting the lowest and highest carbon prices, in general, have lower ROE than for agents with a more accurate carbon price expectation (*b*=0.5 or 1.0).

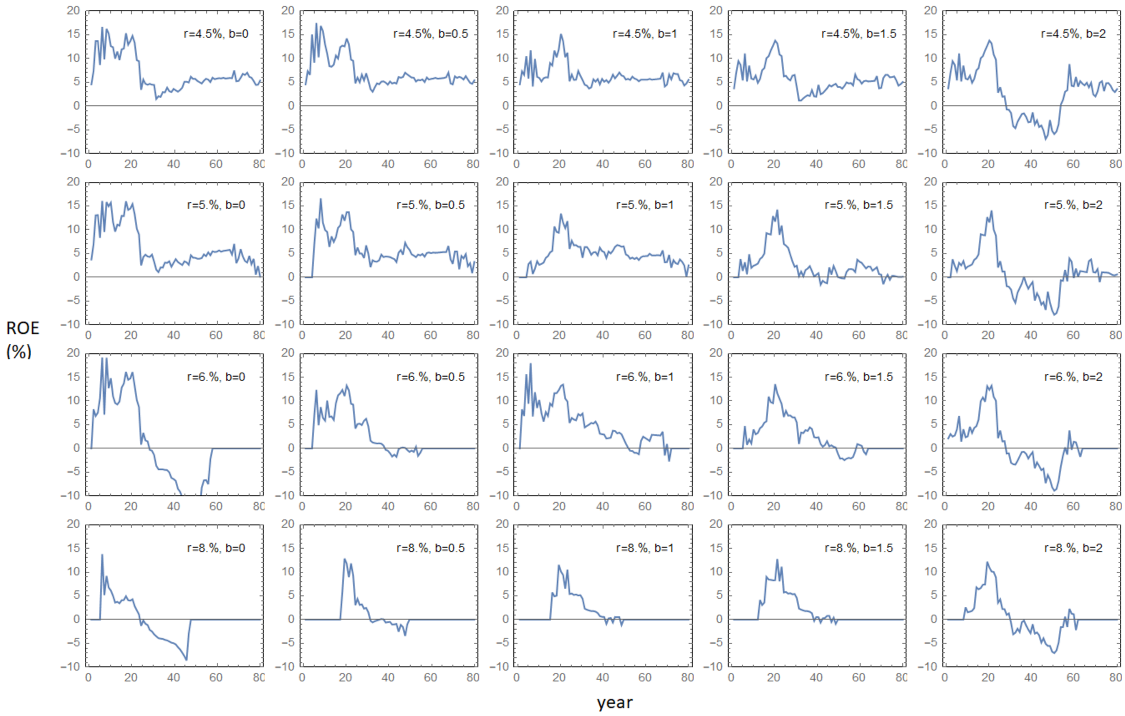


Figure 16 Return on equity (ROE) for all agents over the full time period of 80 years (base case, f=30%, and i=400). r is the hurdle rate used by the agent and b reflects the agent’s expectation on the carbon price. See Eq. 1 for a detailed explanation of *b.*

When applying stochastic fuel prices and electricity demand in the model, results show that all agents experience a higher risk of going bankrupt as a whole because agents then make investments under a higher degree of uncertainty. However, the agents who expect the lowest or highest carbon price still have the highest risk of bankruptcy (Fig. 17).

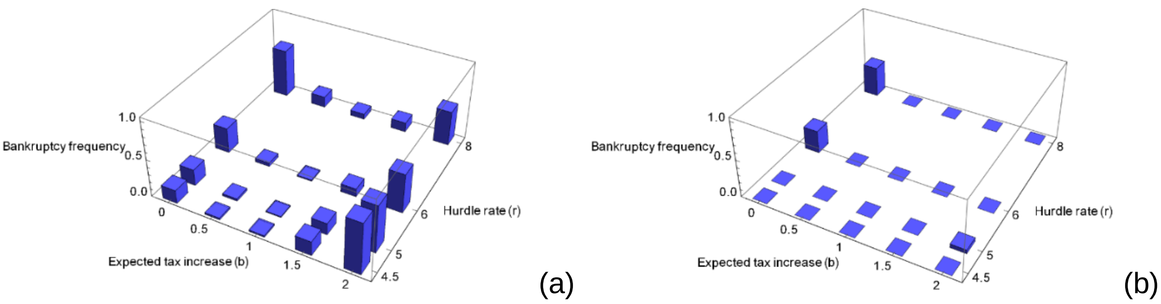


Figure 17 (a) The bankruptcy frequency in the case with stochastic fuel price and energy demand (results from 1000 runs). (b)Bankruptcy frequency in the base case (f =30% and i= 400M€). With stochastic fuel prices or electricity demand, agents are more likely to go bankrupt.

7. Conclusions and Discussions

Using an agent-based model approach, we have analysed agents' investment decisions in new generating capacity. Centred around three aspects—heterogeneity, uncertainty, and financial feedbacks—this study has explored the transition to a low-carbon electricity system under a scenario with an increasing carbon tax.

Heterogeneity is represented by two characteristics: the hurdle rate that an agent uses and the agent's expectation about future carbon tax levels. Uncertainty is manifested by the limited information (about the system) the agents have and the stochastic fuel price and electricity demand. Financial feedback is created by a loop in which the agents' earlier investments impact the overall system (installed capacity and electricity price), which impacts the agents' revenues in coming years, affecting agents' future investments.

We construct various model set-ups to explore the impact of heterogeneity, uncertainty, and financial feedbacks and how the transition could be enhanced or hampered. Results are analysed on both the system level and on the level of the individual agents. On the system level, we mainly explore the development of the capacity mix, average electricity prices, competition between different technologies, and emission reduction trajectories. On the level of the individual agent, we focus on agents' investment choices and economic performance.

The main contribution of this study is two-fold: to inform policymaking and to advance agent-based modelling. The next section discusses the contribution from these two perspectives, along with the limitations of the current work and research ideas that will tackle some of these current limitations.

7.1. Policy implications

Although countries around the world acknowledge a need to reduce CO_2 emissions, and major emitters have set goals to significantly reduce their emissions (EU-Commission, 2020; The State Council China, 2020; The White House, 2021; UNFCCC, 2015), studies show that the pace of mitigation needs to accelerate in order to meet climate targets (IRENA, 2020b). This study has touched on potential ways that could help speed up the emissions mitigation process, from an investment perspective.

First, this study has analysed how different levels of perceived risk (measured by the hurdle rate used by agents) impact investors' investment decisions. Agents who use lower hurdle rates are more willing to invest, which leads to emissions being reduced faster. This implies that policymakers may want to consider ways to reduce investment risks for low-carbon technologies, especially if these policymakers are not able to apply sufficiently high carbon taxes.

Our results have also shown that agents who expect high carbon prices start to invest early and are more willing to invest in low-carbon technologies. This implies that the mitigation process may speed up if a government can provide a clear signal of an increasing carbon price or promise a more stringent emission cap.

Additionally, our results have demonstrated that the finanancial constraint (and access to capital) is a critical issue for the transition to a low-carbon system. With fewer financial constraints, the transition will be faster. This implies that policymakers may want to consider incentivising more access to capital for low-carbon technologies. This can be particularly relevant for the Global South, where the financial market is less developed.

7.2. Development of models methods

This study also contributes to the modelling community by putting forward new methodologies. First, this study (Paper II) uses an explicit way of modelling financing (for power plants). Most energy system models do not model financing explicitly. Our model includes an explicit treatment of how power sector investments are financed and how a company's economic performance affects the possibility for future investments.

Second, in many energy models, especially in optimisation models, investment constraints (i.e., the annual investment limit) are set arbitrarily, while this study proposes a more natural way of treating investment constraints. The investment is explicitly constrained by financial constraints and an agent’s access to capital (how much money a company can borrow and the initial capital a company has).

This study also contributes to a better understanding of the impact of different parameter assumptions. When modelling (the energy system), modellers have to make decisions about certain parameters. However, whether these assumptions are reasonable and what their impacts are is not always thoroughly studied. This study has tested different assumptions for several parameters, such as the hurdle rate (discount rate) and the access to capital.

7.3. Limitations of this study

Due to simplifications made in the model, this study has limitations. This section reflects on the simplifications in the current model. We plan to address some of these limitations in our future studies.

First, the model simplifies the investment decision process. In our model, the decision criteria are simplified as a net present value calculation of individual investments. However, in reality, an investor may take into account many other factors simultaneously, such as payback time, the entire plant portfolio, and specific investment preferences. Moreover, the heterogeneity of agents, in reality, involves more aspects. In addition to what we have in our model, (heterogeneous hurdle rates and carbon price expectation), real agents are also heterogeneous in starting point (such as capacity and portfolio), previous experiences, investment purposes, etc. These factors may impact an investor’s investment decisions.

Second, an agent in our model applies the same hurdle rate for different types of projects/technologies, and the bank uses the same interest rate for all investments, whereas in reality, hurdle rates and interest rates may vary depending on individual projects and investors. Moreover, the hurdle rate and the interest rate may also vary from year to year.

Given the fact that the energy transition is a highly complex process, our model certainly involves additional simplifications. However, since the agent-based model has the advantages of directly implementing assumed mechanisms, it is relatively straightforward to include additional mechanisms to the model, and some of the limitations mentioned above will be addressed directly in our next model extension project. (See discussion below.)

7.4. Key research questions moving forward

Followed by this licentiate thesis, the research will move forward in two ways. First, the HAPPI model will be further developed. To better reflect real investment decision-making, one extension of the model is to have agents with specific investment preferences. For example, some agents would only invest in wind and/or solar, while some agents prefer to invest in coal and gas power plants. Another extension of the model is to have adaptive agents, which means the agents will adjust their investment criteria based on previous investment outcomes.

Second, we will continue to explore the energy system transition. One interesting topic is the technology learning curve. The costs of low-carbon technologies decrease due to learning-by-doing process. In the next model version, the investment cost will be modelled as an explicit function of installed capacity. We will investigate whether "early-mover" or "late-adopter" is the better investment strategy.

References

[1] Arthur, W.B., 2021. Foundations of complexity economics. Nature Reviews Physics 3, 136-145.

[2] Bale, C.S.E., Varga, L., Foxon, T.J., 2015. Energy and complexity: New ways forward. Applied Energy 138, 150-159.

[3] Barazza, E., Strachan, N., 2020. The impact of heterogeneous market players with bounded-rationality on the electricity sector low-carbon transition. Energy Policy 138, 111274.

[4] Battiston, S., Monasterolo, I., Riahi, K., van Ruijven, B.J., 2021. Accounting for finance is key for climate mitigation pathways. Science, eabf3877.

[5] Bonabeau, E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences 99, 7280-7287.

[6] BP, 2020. bp Statistical Review of World Energy June 2020, BP p.l.c. website.

[7] Brown, T., Reichenberg, L., 2021. Decreasing market value of variable renewables can be avoided by policy action. Energy Economics 100, 105354.

[8] Calder, M., Craig, C., Culley, D., de Cani, R., Donnelly, C.A., Douglas, R., Edmonds, B., Gascoigne, J., Gilbert, N., Hargrove, C., Hinds, D., Lane, D.C., Mitchell, D., Pavey, G., Robertson, D., Rosewell, B., Sherwin, S., Walport, M., Wilson, A., 2018. Computational modelling for decision-making: where, why, what, who and how. Royal Society Open Science 5, 172096.

[9] Chappin, E.J.L., de Vries, L.J., Richstein, J.C., Bhagwat, P., Iychettira, K., Khan, S., 2017. Simulating climate and energy policy with agent-based modelling: The Energy Modelling Laboratory (EMLab). Environmental Modelling & Software 96, 421-431.

[10] Cherp, A., Vinichenko, V., Jewell, J., Brutschin, E., Sovacool, B., 2018. Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework. Energy Research & Social Science 37, 175-190.

[11] Desouza, K.C., Lin, Y., 2011. Towards Evidence-Driven Policy Design: Complex Adaptive Systems and Computational Modeling. The Innovation Journal 16(1).

[12] Eberlen, J., Scholz, G., Gagliolo, M., 2017. Simulate this! An Introduction to Agent-Based Models and their Power to Improve your Research Practice. Int Rev Soc Psychol 30, 149-160.

[13] EU-Commission, 2020. 2050 long-term strategy, Climate strategies & targets. EU Commission, https://ec.europa.eu/clima/policies/strategies/2050_en.

[14] European Commission, 2015. EU ETS Handbook. European Union, https://ec.europa.eu/clima/sites/clima/files/docs/ets_handbook_en.pdf.

[15] Galan, J.M., Izquierdo, L.R., Izquierdo, S.S., Santos, J.I., del Olmo, R., Lopez-Paredes, A., Edmonds, B., 2009. Errors and Artefacts in Agent-Based Modelling. Jasss-J Artif Soc S 12.

[16] Gerst, M.D., Wang, P., Roventini, A., Fagiolo, G., Dosi, G., Howarth, R.B., Borsuk, M.E., 2013. Agent-based modeling of climate policy: An introduction to the ENGAGE multi-level model framework. Environmental Modelling & Software 44, 62-75.

[17] Gilbert, N., Ahrweiler, P., Barbrook-Johnson, P., Narasimhan, K.P., Wilkinson, H., 2018. Computational Modelling of Public Policy: Reflections on Practice. Jasss-J Artif Soc S 21.

[18] Gooding, T., 2019. Agent-Based Model History and Development, Economics for a Fairer Society: Going Back to Basics using Agent-Based Models. Springer International Publishing, Cham, pp. 25-36.

[19] Goulder, L.H., Schein, A.R., 2013. CARBON TAXES VERSUS CAP AND TRADE: A CRITICAL REVIEW. Climate Change Economics 4, 1-28.

[20] Government of Canada, 2021. Mathematical modelling and COVID-19, https://www.canada.ca/en/public-health/services/diseases/coronavirus-disease-covid-19/epidemiological-economic-research-data/mathematical-modelling.html.

[21] Government Office for Science, 2018. Computational Modelling: Technological Futures, in: Science, U.G.O.f. (Ed.), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/682579/computational-modelling-blackett-review.pdf.

[22] Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Pe’er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R.A., Vabø, R., Visser, U., DeAngelis, D.L., 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling 198, 115-126.

[23] Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F., 2010. The ODD protocol: A review and first update. Ecological Modelling 221, 2760-2768.

[24] Grimm, V., Railsback, S.F., Vincenot, C.E., Berger, U., Gallagher, C., DeAngelis, D.L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., uuml, rgen, Johnston, A.S.A., Milles, A., Nabe-Nielsen, J., Polhill, J.G., Radchuk, V., Rohw, auml, der, M.-S., Stillman, R.A., Thiele, J.C., Ayll, oacute, n, D., 2020. The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism. Journal of Artificial Societies and Social Simulation 23, 7.

[25] Hansen, P., Liu, X., Morrison, G.M., 2019. Agent-based modelling and socio-technical energy transitions: A systematic literature review. Energy Research & Social Science 49, 41-52.

[26] Hirth, L., 2013. The market value of variable renewables: The effect of solar wind power variability on their relative price. Energy Economics 38, 218-236.

[27] Horschig, T., Thrän, D., 2017. Are decisions well supported for the energy transition? A review on modeling approaches for renewable energy policy evaluation. Energy, Sustainability and Society 7, 5.

[28] IEA, 2019. Global Energy & CO2 Status Report 2019. International Energy Agency, Paris.

[29] IEA, 2020. CO2 Emissions from Fuel Combustion: Database Documentation. International Energy Agency, Paris, p. 17.

[30] IEA, 2021. CO2 emissions by energy source, World 1990-2018 International Energy Agency, Paris.

[31] IPCC, 2014a. Climate Change 2014: Synthesis Report, the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland, p. 45.

[32] IPCC, 2014b. Energy Systems, Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Cambridge, United Kingdom and New York, USA.

[33] IRENA, 2019. NDCs in 2020: Advancing renewables in the power sector and beyond. International Renewable Energy Agency, Abu Dhabi.

[34] IRENA, 2020a. Global Renewables Outlook: Energy Transformation 2050 (2020 edition). International Renewable Energy Agency, Abu Dhabi.

[35] IRENA, 2020b. Renewable energy finance: Institutional capital International Renewable Energy Agency, Abu Dhabi.

[36] IRENA and CPI, 2020. Global Landscape of Renewable Energy Finance 2020. International Renewable Energy Agency and Climate Policy Initiative, Abu Dhabi, p. 35.

[37] Jonson, E., Azar, C., Lindgren, K., Lundberg, L., 2020. Exploring the competition between variable renewable electricity and a carbon-neutral baseload technology. Energy Systems 11, 21-44.

[38] Kahneman, D., 2011. Thinking, Fast and Slow. Farrar, Straus and Giroux, United States.

[39] Klein, M., Frey, U.J., Reeg, M., 2019. Models Within Models – Agent-Based Modelling and Simulation in Energy Systems Analysis. Journal of Artificial Societies and Social Simulation 22, 6.

[40] Köhler, J., de Haan, F., Holtz, G., Kubeczko, K., Moallemi, E., Papachristos, G., Chappin, E.J.L., 2018. Modelling Sustainability Transitions: An Assessment of Approaches and Challenges. Journal of Artificial Societies and Social Simulation 21, 8.

[41] Kraan, O., Kramer, G.J., Nikolic, I., 2018. Investment in the future electricity system - An agent-based modelling approach. Energy 151, 569-580.

[42] Laubenbacher, R., Hinkelmann, F., Oremland, M., 2013. Chapter 5 - Agent-Based Models and Optimal Control in Biology: A Discrete Approach, in: Robeva, R., Hodge, T.L. (Eds.), Mathematical Concepts and Methods in Modern Biology. Academic Press, Boston, pp. 143-178.

[43] Li, F.G.N., 2017. Actors behaving badly: Exploring the modelling of non-optimal behaviour in energy transitions. Energy Strategy Reviews 15, 57-71.

[44] Li, F.G.N., Strachan, N., 2019. BLUE: Behaviour Lifestyles and Uncertainty Energy model, Online Documentation Revision 04, Version 2.3 ed, https://www.ucl.ac.uk/energy-models/sites/energy-models/files/2019-01-16_blue_v2.3_documentation.pdf.

[45] Loomis, J., Bond, C., Harpman, D., 2008. The Potential of Agent-Based Modelling for Performing Economic Analysis of Adaptive Natural Resource Management. Journal of Natural Resources Policy Research 1, 35-48.

[46] López Prol, J., Steininger, K.W., Zilberman, D., 2020. The cannibalization effect of wind and solar in the California wholesale electricity market. Energy Economics 85, 104552.

[47] Ma, T., Nakamori, Y., 2009. Modeling technological change in energy systems – From optimization to agent-based modeling. Energy 34, 873-879.

[48] Manzo, G., 2014. Potentialities and Limitations of Agent-based Simulations. An introduction. Revue française de sociologie 55, 653-688.

[49] NOAA, 2021. Trends in Atmospheric Carbon Dioxide. National Oceanic and Atmospheric Administration, https://www.esrl.noaa.gov/gmd/ccgg/trends/mlo.html.

[50] Partridge, J., 2020. World's biggest fund manager vows to divest from thermal coal, The Guardian. The Guardian, https://www.theguardian.com/business/2020/jan/14/blackrock-says-climate-crisis-will-now-guide-its-investments.

[51] Quinson, T., Benhamou, M., 2021. Banks Always Backed Fossil Fuel Over Green Projects—Until This Year, Bloomberg Green. Bloomberg, https://www.bloomberg.com/graphics/2021-wall-street-banks-ranked-green-projects-fossil-fuels/.

[52] Schelling, T.C., 1971. Dynamic Models of Segregation. J Math Sociol 1, 143-186.

[53] Sepulveda, N.A., Jenkins, J.D., de Sisternes, F.J., Lester, R.K., 2018. The Role of Firm Low-Carbon Electricity Resources in Deep Decarbonization of Power Generation. Joule 2, 2403-2420.

[54] Thaler, R.H., Sunstein, C.R., 2008. Nudge: Improving Decisions about Health, Wealth, and Happiness. Yale University Press, United States.

[55] the Australian Government, 2020. Update: Modelling the current impact of COVID-19 in Australia, https://www.health.gov.au/resources/publications/update-modelling-the-current-impact-of-covid-19-in-australia.

[56] The State Council China, 2020. Carbon mitigation, China has set concrete targets. The State Council China, http://www.gov.cn/xinwen/2020-09/30/content_5548478.htm.

[57] the UK Government, 2021. Scientific evidence supporting the government response to coronavirus (COVID-19) Coronavirus (COVID-19) Rules, guidance and support https://www.gov.uk/government/collections/scientific-evidence-supporting-the-government-response-to-coronavirus-covid-19#modelling-inputs.

[58] The White House, 2021. FACT SHEET: President Biden Sets 2030 Greenhouse Gas Pollution Reduction Target Aimed at Creating Good-Paying Union Jobs and Securing U.S. Leadership on Clean Energy Technologies https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/fact-sheet-president-biden-sets-2030-greenhouse-gas-pollution-reduction-target-aimed-at-creating-good-paying-union-jobs-and-securing-u-s-leadership-on-clean-energy-technologies/.

[59] the World Bank, 2021. Carbon Pricing Dashboard, https://carbonpricingdashboard.worldbank.org/map_data.

[60] UNFCCC, 2015. Paris Agreement. United Nations, https://unfccc.int/sites/default/files/english_paris_agreement.pdf.

[61] Zhai, Y., Mo, L., Rawlins, M., 2018. The Impact of Nationally Determined Contributions on the Energy Sector: Implications for ADB and Its Developing Member Countries, Sustainable Development Working Paper Series. Asian Development Bank, Manila, Philippines.

Appendix - detailed model description

HAPPI - Model documentation

In this section, we present the HAPPI (Heterogeneous Agent-based Power Plant Investment) model following the ODD protocol (Overview, Design Concepts, and Details) (Grimm et al., 2006; Grimm et al., 2010; Grimm et al., 2020). The ODD protocol aims to provide a standardised way of describing simulation models, such as autonomous individual organisms (IBM) or agent-based models (ABM), and to make the models easier to understand and replicate (Grimm et al., 2006). We describe our model by going through all seven elements in the protocol.

1. Purpose

The overall purpose of the model is to study the transition of the electricity sector to a low-carbon system. Specifically, we focus on the decision-making criteria of the agents, which are power companies that invest in new generation capacity. We analyse how the electricity system develops over time given climate policy measures.

2. Entities, state, variables, scales

The model includes two types of entities. The first is the power company. Power companies are characterised by two attributes, the hurdle rate each agent uses (denoted by r in the model), and the expectation of future carbon tax each agent has (reflected by b in the model). A hurdle rate is the minimum rate of return on an investment required by a company, indicating a company's risk management. The higher r a company employs (for evaluating an investment option), the higher risk the investor perceives. The value of b for a given company reflects whether the company thinks the carbon tax will increase faster or slower than it actually ends up doing.

The second entity is the power plant. There are six types of power plants in the model: coal-fired, gas-fired, gas-fired with carbon capture and storage (gasCCS), nuclear, solar PV, and wind power. The plants are characterised by six attributes: fuel type, investment cost, size, carbon emission intensity, fuel cost, and lifespan.
The temporal resolution of the model is one year, and each year is divided into 64 slices (detailed information about the slice can be found in the section "Input data"). We run the model for a total of 80 years.

3. Process overview, scheduling

In each time step, we simulate two types of decisions that each agent makes. First, the individual company makes decisions about electricity production. Companies produce electricity from power plants that have operation costs lower than or equal to the electricity price. The electricity price is calculated based on an iso-elastic demand function.

The second decision is the investment decision. Each year, plants that reach the end of their lifespan get decommissioned, and agents take turns making investment decisions on new generation capacity, based on expected investment profits. After all the companies are done making their investments, the model goes to the next year.

State variables are updated both on the individual company level and the system level. On the company level, the individual installed capacity and financial performance (money in the bank account and equity) are updated. If a company's equity goes below zero, it goes bankrupt and is not allowed to make further investments. On the system level, aggregated installed capacity is updated annually. We also make ex-post calculations of the Internal Rate of Return (IRR) of each investment, averaged annual electricity price, electricity production profile, and emission trajectories.

4. Design concept

Basic principles

The electricity system transits to a low-carbon system under a growing carbon tax scenario.

Emergence

The development of the capacity mix on the system level emerges as a result of individual companies' new investments and the exit of obsolete plants. (The transition of the electricity system occurs through this emergence.)

Adaptation

In the current version, there is no adaptation behaviour, but we plan to use adaptive hurdle rates in future versions of the model, which means companies adapt their hurdle rates based on the profitability of their previous investments.

Objectives

The objective of each company is to maximise its profit for each investment. Companies rank the investment options by expected profitability and choose the one with the highest expected profitability. The profitability is based on a Net Present Value (NPV) calculation.

Learning

The current model version does not include a learning process.

Prediction

Companies make two types of predictions. First, they predict future carbon prices. Companies have limited information about future carbon prices. They look n years ahead and predict how fast the tax will grow. Their expectations are given by a growth factor b times the true tax in n years (details in the Section 7 below). Second, taking into account the future carbon tax, agents make predictions about the profitability of potential investment options.

Sensing

Two types of sensing are included in the model. First, companies have information about the carbon tax for the next year. Second, once a company has made an investment decision, information about the type (and size) of the plant is made public immediately.

Interaction

There is no direct interaction among agents/companies. However, the agents interact with each other indirectly via competition. The agents compete with one another in the electricity market by selling electricity and investing in new power plants. If an agent performs poorly (equity goes below zero), it goes bankrupt and is not allowed to make further investments, while agents that perform well accumulate profits over time and take more market share.

Stochasticity

Three stochastic processes are used in the model. First, agents take turns making investment decisions, and the sequence of agents is randomly assigned each year. The second stochastic process is the development of fuel prices over time (coal and gas prices). Finally, the model implements a stochastic electricity demand as well. The second and third stochastic processes can be toggled on or off depending on the case we investigate.

Collectives

The capacity mix on the system level is an aggregation of individual agents' investment decisions, while the capacity mix of the system, in turn, also affects individual agents' new investment decisions via affecting the revenue received with different types of investment choices.

Observation

Data are collected both at the individual agent level and the system level. At the agent level, we collect information on each agent's investment decisions, return on investments, bank account balance, and equity. At the system level, we record capacity mix, electricity production profile, emission trajectory, and averaged annual electricity price. All data are displayed as outputs of the model and illustrated in plots.

5. Initialisation

Power plant

The model starts at year 0 in a stationary state with 64 GW coal and 2 GW gas in the system. Each coal and gas plant has a capacity of 500MW. The initial capacity is comparable with the electricity system in a country like Germany. We separate these initial coal and gas plants and place them in an additional company that does not take part in the investment process, only runs the plants throughout their lifetime.

Companies/Agents

The initial number of companies varies depending on the design of the two company attributes (the hurdle rate r and the expectation of future carbon tax b). The initial number of companies is equal to the number of possible combinations of sets r and b.
For example, let*:*

- $r \in \{4.5\%, 5\%, 6\%, 8\%\}$ per year
- $b \in \{0, 0.5, 1.0, 1.5, 2.0\}$

Then there are 20 combinations of r and b, plus one additional company that owns the initial plants but does not invest; therefore, there are 21 companies in total.

Stochastic process

The stochastic process of the fuel price (gas and coal prices) and the electricity demand can be set to either On or Off. The stochastic process is off if the parameter value is set to 0, and it is on if the value is greater than 0 (see Section 7 for details).

Financial module

Several parameters regarding the financial settings need to be initialised.

- f : the investment fraction paid from a company's capital
- f_{div}: dividend fraction
- i: initial capital in a company's bank account
- m_{save}: a company's reserved amount after the dividend is paid

Example:

- $f = 30\%$.
- $f_{div} = 50\%$.
- $c_{initial} = 400$ M€.
- $m_{save} = 1500$ M€.

See Section 7 for more details about the financial module.

6. Input data

The model uses several external input data. These are time-series data used to 'drive' the model. First, the tax scenario is given externally. In our base case, the carbon tax is 0 €/ton in the first ten years, and then it increases by 2€/ton per year and reaches at 100 €/ton in year 60, remaining at 100 €/ton afterwards. Second, the electricity demand, wind availability, and solar availability are also external data. The detailed values are provided in the table in the Appendix A2.

7. Submodels

This section describes all processes listed in the "process overview and scheduling" section.

Electricity production and price

The companies produce electricity in an ideal electricity market. They produce electricity so long as the electricity price is greater than (or equal to) the running cost of their plants, following the merit order. The electricity price and production quantity are determined by an iso-elastic demand function:

$$q_\tau = q_{0,\tau} \times \left(\frac{p_\tau}{p_0}\right)^\epsilon \quad (1)$$

where p_τ is the electricity price in time slice τ, which is reached when the electricity produced (and consumed) q_τ meets the demand. The reference demand $q_{0,\tau}$ is given and reflects the varying demand over different time slices in Germany in 2011. The reference electricity price is $p_0 = 3.25€\text{ct/kWh}$, and the elasticity is $\varepsilon = -0.05$ (Jonson et al., 2020). One year consists of time 64 slices with various hours (in Appendix Table A1). The average electricity price presented in the main paper is a production-weighted average price.

The expectation of future tax prediction

Companies have limited information about future carbon prices. They know the true carbon tax of next year, and they estimate the tax level n years ahead. Their expectations, denoted $F_b(t+n)$, are given by the true tax in the next year $T(t+1)$ plus a factor b times the difference between the true tax $T(t+n)$ in n years time and $T(t+1)$:

$$F_b(t+n) = T(t+1) + b\big(T(t+n) - T(t+1)\big) \tag{2}$$

We use a set $\{0, 0.5, 1.0, 1.5, 2.0\}$ for b, which means agents' expectations regarding the rate at which the carbon tax will increase range from zero times the actual increase to twice as high as the actual increase. Agents assume that the tax stays the same as $F_b(t+n)$ afterwards.

Financial performance – the financial module

This module keeps track of each agent's financial status, and this, in turn, is used to determine whether an agent can afford to make further investments. We use the following mechanism in our approach: First, an agent is assumed to pay a certain fraction f of a new investment from its bank account, the remaining part of the investment, $(1-f)$, is paid by a loan from the bank with an interest rate r_l. Second, the agent's bank account can accumulate profit from the company's plant operations, and a certain fraction f_{div} of the capital can be paid to the shareholders as dividend d, provided that the planned investments for coming years can be made, as described below. There is no interest on the bank account, but if the money in the bank account were to go below 0, this is regarded as an ordinary loan with interest r_l.

We add the following variables characterising the state of a company and the requirements for new investments:

1. The value of a company is assumed to be the total value of its plants V plus the bank account holdings M less the debt D to the bank. This is the equity E of the company. If the equity goes below 0, the company is bankrupt.
$$E = V + M - D \tag{3}$$

2. From one year to the next, the money in the bank account changes due to net revenues R_{net} (defined as revenues from selling electricity less operating costs), investment costs I, interest costs $C_{l,f}(t)$, repayment of loans $L_{l,f}(t)$, and dividend d paid to shareholders,
$$M(t+1) - M(t) = R_{net}(t) - f \cdot I(t) - C_{l,f}(t) - L_{l,f}(t) - d(t) \tag{4}$$

   Note that $C_{l,f}$ and $L_{l,f}(t)$ together are given by $(1-f)A_i$, where A_i is the sum of all annuitized costs of the standing plants, since the fraction $(1-f)$ of an investment is financed by a loan. Similarly, investment costs $f \cdot I$ are a fraction of full investment costs, where I is the sum of full investment cost for plants in a specific year. A company is not allowed to invest if the money in the bank account goes below 0.

   The dividend d is paid according to the following the rules:

   a. First, investments are made according to the company's rules of operation.

b. A given amount m_{save} is reserved to allow for a future (hypothetical) investment in the most expensive plant. This means that a dividend is not paid in general and especially not in the initial years when the companies are in a growth phase.
c. Up to a fraction f_{div} of the money in the bank account is paid to the shareholders as a dividend, but not more than that m_{save} is kept, i.e., $d = Min(f_{div}M, M - m_{save})$.

3. The total value of a company's plants, V, changes due to new investments I and capital depreciation of plants, C_{depr},

$$V(t+1) - V(t) = I(t) - C_{depr}(t)\,. \tag{5}$$

Each plant has a value V_{plant} that initially is equal to its investment cost and from then on equals the remaining debt that one would have if one were (hypothetically) to have borrowed the full investment at an interest r_l and paid the annualised capital cost every year. The value $V_{plant}(t_R)$ of the plant with a remaining lifetime t_R can then be expressed as

$$V_{plant}(t_R) \;= I_{plant}\,\frac{1-(1+r_l)^{-t_R}}{1-(1+r_l)^{-t_L}} \tag{6}$$

where I_{plant} is the plant investment cost and t_L is the full lifetime.

4. The debt D changes due to new loans taken and repayment of present loans $L_{l,f}$. New loans are taken to cover $(1-f)$ of investment costs, so the change in debt is then

$$D(t+1) - D(t) = (1-f)I(t) - L_{l,f}(t)\,. \tag{7}$$

5. By combining Eqs. (3,4,6,7), we get the change in equity

$$E(t+1) - E(t) = R_{net}(t) - C_{l,f}(t) - C_{depr}(t) - d(t). \tag{8}$$

Note that, since we give the value of the plants according to Eq. 6, the capital depreciation equals the repayment of a hypothetical loan for full investment costs.

Investment decisions

There are six types of power plants that a company can choose to invest in, namely, coal-fired, gas-fired, gas-fired with carbon capture and storage (gasCCS), nuclear, solar PV, and wind power. The parameter settings of the plant are listed in Table A3.

Each year, plants that reach the end of their lifespan are decommissioned, and companies invest in new capacity. The model removes one retiring plant at a time. Following a plant removal, the agents take turns (the order is random) to make investment decisions for new plants. The decision process follows the following steps. First, an agent adds a hypothetical power plant (testing all the six available technologies) to the existing capacity mix. Taking into account the expected CO_2 tax in the following n years, e.g. n= 10 years (How agents form the tax expectation is described in Eq. 2), the agent then calculates the electricity price (Eq. 3), production profile, and the expected annual profit of this newly added plant for the next n

years. The agent assumes that for the rest of the lifetime of this plant, the annual profit will be the same as what the agent estimated for year n. Lastly, after evaluating every available technology, the agent chooses the technology with the highest positive *profitability index* (Eq. 9 and Eq. 10) to invest in, given the condition that this agent can provide the required payment fraction f from its own bank account. If the agent cannot afford the payment, then it will not invest in the current round.

$$profitability\ index = \frac{NPV}{I} \times CRF \tag{9}$$

$$NPV = \sum_{t=1}^{T} \frac{R_t - C_t}{(1+r)^t} - I \tag{10}$$

$$CRF = \frac{r}{1-(1+r)^{-T}} \tag{11}$$

where NPV is the net present value of all future revenues and costs, T is a plant's lifespan, and R_t and C_t are the revenues and costs at year t. The plant's investment cost is I, and r is the hurdle rate used by the agent. The capital recovery factor (CRF) is used because different power plants have different lifespans.

In the present version of the model, if the agent cannot afford the payment to invest in the top NPV-ranked power plant, then it will not invest in the current round.

Stochastic processes

In the current model version, three parameters can change stochastically over time. They are the gas price, coal price, and electricity demand. A first-order autoregressive model (AR1) determines the parameter value (Eq. 12).

$$x_{t+1} = x_t + \varepsilon_1(\bar{x} - x_t) + \varepsilon_2 \cdot z_{t+1} \tag{12}$$

where x_t is the parameter value of the current time step, and x_{t+1} is the parameter value of the next time step. $\bar{x}$ is the average value of the parameter x_t. AR parameters are denoted by ε_1 and ε_2. The stochasticity comes from the random term z_{t+1}, a real-valued random number which ranges from -1 to +1.

Internal Rate Return

The internal rate of return (*IRR*) of an individual investment is calculated ex-post and IRR is the solution to the equation,

$$0 = \sum_{t=1}^{T} \frac{R_{net}}{(1+IRR)^t} - I_{plant}\ , \tag{13}$$

Where T is a plant's lifespan, R_{net} is the net revenues in year t, and I_{plant} is the investment cost of the plant.

Return on equity

We use the return on equity *ROE* given by net revenues R_{net} (revenues from selling electricity less operating costs) less interest $C_{l,f}$ and depreciation costs C_{depr} divided by equity E,

$$ROE = \frac{R_{net} - C_{l,f} - C_{depr}}{E} \tag{14}$$

i.e., net profit divided by equity. In case there is no dividend paid, $R_{net} - C_{l,f} - C_{depr}$ is the change in equity from one year to the next, see Eq. (8). *ROE* thus quantifies the equity growth (before the dividend is paid).

8. Other parameter settings

Time slicing

Table A1. The number of hours in each of the time slices (adapted from Jonson et al. 2020).

		Low wind	Medium-low wind	Medium-high wind	High wind
Low solar	Low q0	28	146	65	25
	Medium-low q0	256	1027	751	283
	Medium-high q0	153	645	434	255
	High q0	16	63	70	73
Medium-low solar	Low q0	34	128	53	21
	Medium-low q0	104	398	213	72
	Medium-high q0	59	268	235	119
	High q0	10	34	33	46
Medium-high solar	Low q0	24	35	19	7
	Medium-low q0	124	227	163	81
	Medium-high q0	264	703	419	138
	High q0	17	52	89	53
High solar	Low q0	0	0	0	0
	Medium-low q0	23	15	15	1
	Medium-high q0	48	102	10	8
	High q0	1	3	2	0

Solar availability and wind availability

Table A2. Reference demand, solar availability, and wind availability

	Low level	Medium-low level	Medium-high level	High level
Reference demand *q0* (GW)	37.3060	47.6100	63.2400	71.5555
Solar availability	0	0.0311	0.3439	0.6731
Wind availability	0.0689	0.1912	0.4282	0.7470

Power plant parameters

Table A3. Power plants parameters – costs and efficiencies

Plant type	Capacity (unit size) (MW)	Running cost (euro cents/kWh)	Investment cost (euro/kW)	Lifetime (years)	Emission intensity (gCO_2/kWh)
Coal	500	2.0	1500	40	1000
NGCC	500	4.6 [3] (natural gas)	900	30	432
		8.0 (biogas)			0
NGCC with CCS	500	5.83[4]	1400	30	51
Nuclear	500	1.0	6000	40	0
Solar PV	500	0	800	25	0
Wind	500	0	1500	25	0

[3] Running cost (NGCC) = fuel cost / efficiency = fuel cost / 46.7% = 4.6 euro cents/kWh

[4] Running cost (NGCC with CCS) = fuel cost / efficiency + storage cost = running cost (NGCC) *46.7%/40%+4.57