THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Exploring the Transition to a Low-Carbon Electricity System — Using Agent-Based Modeling

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ABSTRACT

The ability to produce electricity has profoundly shaped human lives. Over time, the sources used for electricity generation have undergone several transitions. Currently, we are navigating a pivotal shift in the electricity system – decarbonization – a journey fraught with a myriad of challenges. A key challenge is that shifting to a low-carbon electricity system necessitates vast investments. The capital allocation decisions made today will influence global electricity production and associated emissions for the coming decades.

In this thesis, we have developed and employed an agent-based model of investments in the electricity system, called the HAPPI model (Heterogeneous Agent-based Power Plant Investment). The HAPPI model underscores the importance of factoring in heterogeneity, uncertainty, financial feedback, risk aversion, and adaptivity when modeling investment decisions in low-carbon transitions. This thesis primarily analyzes the influence of five important factors on investment decisions: *hurdle rate, future carbon price expectation, access to capital, risk-aversion level,* and *adaptability*. The findings provide insights at both the system and individual agent (investor) levels.

On the system level, the research explores the evolution of generation capacity mix, electricity prices, CO_2 emissions, and the distribution of revenue across diverse technologies. Results show that, with growing carbon prices, there is a notable expansion in the capacity of wind, solar, and nuclear power plants, and a gradual phase-out of coal power plants. On the agent level, the research explores the investment decisions of heterogeneous investors and the associated financial outcomes. Key observations highlight that agents with lower hurdle rates or lower risk or loss aversion tend to invest more, thereby enhancing their profits. However, this increased investment rate is associated with elevated bankruptcy risks, underscoring the intrinsic risk-return trade-off.

Moreover, the findings reveal that the low-carbon transition accelerates when investors have more access to capital. The transition is also expedited when uncertainty around future carbon prices is reduced, expectations for future prices are higher, and aversion to risk or losses diminishes.

Keywords: low-carbon transition, agent-based modeling, energy system modeling, investment decisions, electricity market, open-source model

LIST OF PUBLICATIONS

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Yang, J., Azar, C., & Lindgren, K. (2021). Modelling the Transition towards a Carbon-Neutral Electricity System—Investment Decisions and Heterogeneity. *Energies*, 15(1), 84.

II Yang, J., Azar, C., & Lindgren, K. (2021). Financing the transition toward carbon neutrality—An agent-based approach to modeling investment decisions in the electricity system. *Frontiers in Climate*, 3, 738286.

III Yang, J., Fuss, S., Johansson, D. J., & Azar, C. (2023). Investment Dynamics in the Energy Sector under Carbon Price Uncertainty and Risk Aversion. *Energy and Climate Change*, 100110.

IV Yang, J., Johansson, D. J. (2023). Adapting to Uncertainty: Modeling Adaptive Investment Decisions in the Electricity System. *Under review*.

Author contributions:

Paper I: 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, analyzed the results, and wrote the paper.

Paper II: 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 analyzed the results. JY wrote the original draft with contributions from CA and KL.

Paper III: SF, JY and DJ conceived the idea, with contributions from CA. JY further developed the model. All authors designed model experiments and analyzed the results. JY wrote the original draft, and SF, DJ, and CA reviewed and edited the draft.

Paper IV: JY and DJ conceived the idea. JY further developed the model. Both authors designed model experiments and analyzed the results. JY wrote the original draft with contributions from DJ. Both authors edited and reviewed the paper.

Additional publication co-authored by Jinxi Yang but not included in the thesis:

de Godoy, J., Otrel-Cass, K., Gorroño-Albizu, L., & Yang, J. (2022). Reflection through Diffraction: Interdisciplinarity in Energy Science. Knowledge Cultures, 10(2).

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Gothenburg, Sweden

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TABLE OF CONTENTS

1. Introductifon

1.1 Motivation and Aim

"Investment is the lifeblood of the global energy system. Individual decisions about how to direct capital to various energy projects… (combine to) shape global patterns of energy use and related emissions for decades to come…. Understanding the energy investment landscape today and how it can evolve to meet decarbonization goals are central elements of the energy transition…" – International Energy Agency and International Renewable Energy Agency (2017).

In response to climate change and energy security concerns, the electricity sector has embarked on a transition toward a low-carbon system. Across the globe, nations have set targets to significantly reduce their greenhouse gas emissions, as reflected in their Nationally Determined Contributions (NDCs) to the United Nations Framework Convention on Climate Change (UNFCCC secretariat 2022).

Despite these objectives, the path to this transition is fraught with challenges. According to the International Renewable Energy Agency (IRENA), achieving the climate goal of limiting global warming to 1.5 °C, will require investments in renewable power generation to surpass USD 1.3 trillion per year from 2023 to 2030 (IRENA and CPI 2023). This stands in stark contrast to the current figure, which in 2022 was about USD 0.5 trillion. Despite the recent surge in investments in wind and solar technologies, a substantial investment gap remains. Given this gap and the urgency of transitioning to a low-carbon electricity system, a thorough analysis of the situation is vital. Several pressing questions need to be addressed, such as:

- Which technologies will be profitable and attractive to invest in?
- How would these investments affect the system transition?
- How can we realize and outline the steps for the transition?
- Which factors influence investors' decisions in the energy sector?
- How do climate policies affect investment decisions and transition speed?
- How would this transition affect the profitability of investments in different technologies from an investor's perspective?

Investigating these questions requires a multidisciplinary research approach. Scholars have applied diverse methodologies from psychology (see e.g. Huijts, Molin, and Steg 2012; Steg, Perlaviciute, and Van der Werff 2015), historical pattern analysis (see e.g. Fouquet 2010; Vinichenko, Cherp, and Jewell 2021), economic and financial analysis (see e.g. Kost et al. 2013; Mazzucato and Semieniuk 2018) to shed light on these complex issues. Energy system models are an invaluable interdisciplinary tool in this context, drawing upon elements from mathematics, economics, computer science, environmental science, and policy studies. Numerous such models have been utilized and examined in scholarly work, as evidenced by the review literature (see e.g. Connolly et al. 2010; Chang et al. 2021; Ringkjøb, Haugan, and Solbrekke 2018).

While energy system models serve as powerful instruments for informing energy policy (Süsser et al. 2021), many models adopt an optimization approach that is directed by a central planner with the aim of minimizing total system costs. However, in liberal markets, investments are usually driven by expected returns and risk profiles and the decisions are taken by heterogenous private entities rather than being taken in a centrally orchestrated plan where information on future prices and costs are perfectly known. Consequently, the energy transition emerges as a 'bottom-up' process led by individual investments. This context requires a modeling perspective that better reflects market complexities and more accurately captures the decision-making process of individual investors.

In this context, agent-based models naturally emerge as a possible approach. An agent-based model is a simulation method where individual entities, called agents, act based on decision rules, often revealing emergent, system-wide behaviors. Existing literature utilizing agent-based modeling techniques indeed highlights 'bottom-up' action by individual investors in the energy sector (see e.g. Barazza and Strachan 2021; Jonson et al. 2020; Chappin et al. 2017; Chen et al. 2018; Kraan, Kramer, and Nikolic 2018). However, the complex nature of the investment decision-making process, which is influenced by multiple factors, still necessitates further exploration.

Thus, based on existing literature, the main aim of this work is to develop agent-based modeling tools that better reflect the decision-making process of investors[1] investing within the electricity sector. A second aim is to investigate how variations in assumptions surrounding this decision-making process affect investment choices and their subsequent influence on the low-carbon transition. Based on these aims we formulate the following objectives:

- Develop the Heterogeneous Agent-based Power Plant Investment (HAPPI) model.
- Utilize the HAPPI model to test and analyze how different factors impact investment decisions and the low-carbon transition of the electricity system.
- In particular, we want to analyze the impact on features such as the generation capacity mix, electricity pricing, carbon dioxide (CO_2) emissions, and the profitability of different types of technologies and investors.

Based on their significance to investment decisions in the electricity system and gaps in existing literature, five key factors affecting investment decisions

[1] In our study, investors are defined as entities who invest in, own and operate power plants.

have been examined across the papers that constitute this thesis. These five key factors are:

- Hurdle rate (Paper I & Paper IV),
- Future carbon price expectations (Paper I & Paper III),
- Access to capital (Paper II),
- Risk and loss aversion (Paper III & Paper IV),
- Learning and adaptation (Paper IV).

Some of these factors function as parameterized inputs to the model, such as hurdle rate and access to capital, while others describe investors' behavior, including future carbon price expectations, risk and loss aversion, and learning and adaptation. For each factor, various assumptions have been evaluated within the model. Their effects have been analyzed at both macroscopic (system-wide) and microscopic (individual agents) levels as shown in Fig.1. The goal is to understand how changes to these factors would impact the outputs of the HAPPI model.

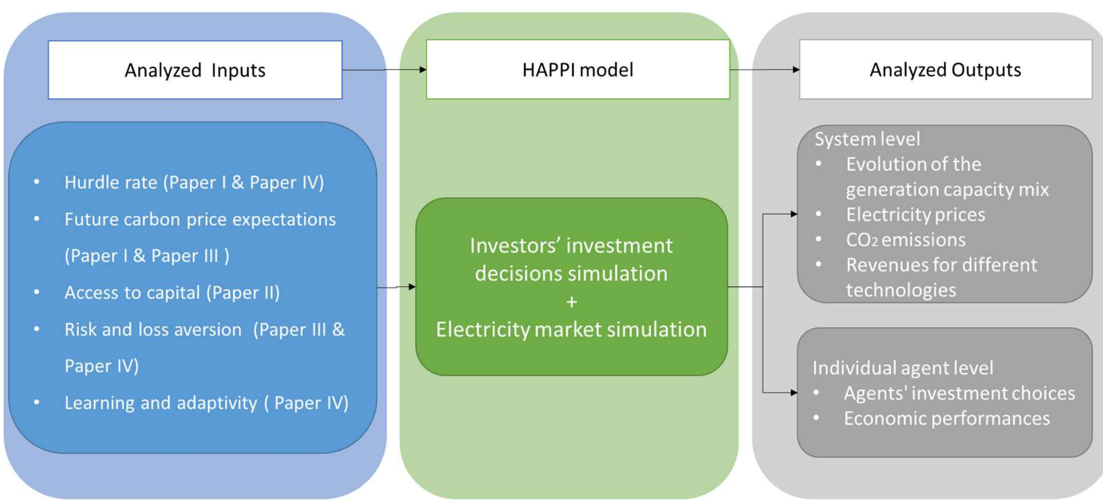


Figure 1. Overview of the thesis. This study utilizes the HAPPI model to analyze varying assumptions related to the five identified factors as model inputs. The resulting impacts are then assessed from two perspectives: a macroscopic viewpoint of the whole system and a microscopic look at individual agents.

1.2 Structure of the Thesis

This thesis comprises four papers, accompanied by an open-source model – HAPPI, which is available at https://github.com/happiABM. Each of the papers focuses on different aspects of model development and associated research questions:

Paper I presents the core model, investigating primary research questions related to the hurdle rate, future carbon tax expectations, agent heterogeneity, and the 'cannibalization effect' of wind energy.

Paper II develops the model further, incorporating a financial module, stochastic fuel prices, and stochastic electricity demand. This paper focuses primarily on how different levels of access to capital impact the agents' investment decisions and economic performances, and how these aspects, in turn, affect the overall development of the electricity system. It also explores which investment strategies can yield strong economic performance (measured by return on equity and bankruptcy rate) under stochastic fuel prices and electricity demand.

Paper III adds a new layer to the model by considering investors' risk and loss aversion, and their investment decisions under carbon price uncertainty. This paper investigates the impact of uncertainty, and of risk as well as loss aversion, on agents' investment decisions and the electricity system's low-carbon transition. The paper also studies how different modeling representations of risk and loss aversion affect the modeling results.

Paper IV introduces adaptive behavior among investors into the model. In this study, agents annually update their hurdle rate based on the historical financial performance of each technology. More specifically: If a technology has proven profitable in the past, it is considered less risky for the investor, with the consequence that the risk premium is smaller and hence the hurdle rate is lowered when evaluating future investments. This paper investigates how investors' adaptive behavior and varying loss-aversion levels impact their investment decisions. The paper also includes stochastic fuel prices, carbon prices, and electricity demand.

In summary, this thesis, through its four papers and the HAPPI model, explores a comprehensive modeling of investment decisions in the electricity system and their consequent impact on the low-carbon transition. With each paper adding a layer of complexity, we move from understanding the fundamental drivers of investment choices to factoring in elements such as financial constraints, risk aversion, and adaptive behavior. This approach is sheds light on the interplay between these factors and their influence on both micro-level investment decisions and the macro-level low-carbon transition in the electricity system. This development and application of the HAPPI model thus represent an innovative approach to understanding and potentially guiding the transition to a low-carbon electricity system.

The remaining sections of this thesis are structured as follows: section two offers a background on the transition of the electricity system, an overview of energy system modeling tools, and an exploration of some key input factors discussed in this thesis. Section three outlines the HAPPI model's development and its features, while also discussing the limitations inherent to our modeling approach. The fourth section presents key findings and a personal reflection and perspective on using agent-based models. The final section summarizes the thesis and offers concluding remarks. The four papers are appended at the end.

2. Background

2.1 Transition of the Electricity System

The ability to produce electricity has profoundly impacted our lives in countless ways, revolutionizing the way we live, work, and communicate. Over the years, the energy sources used for electricity production have undergone several transitions.

In 1882, Thomas Edison opened the first commercial coal-fired power station, which provided electricity for lighting (Pain 2017). Throughout the late 19th century to the early 20th century, coal was the primary energy source for electricity. During the mid-20th century, hydropower gained prominence, especially in regions rich in water resources. During the same period, there was also a shift towards utilizing oil for electricity production, which is noted for its higher energy density and cleaner combustion than coal (Melsted and Pallua 2018). The advent of natural-gas and nuclear power in the late 20th century further diversified energy sources. Although nuclear power came with a promise of abundant and emission-free energy, its popularity declined due to concerns surrounding safety, waste disposal, and high-profile accidents, such as those at Chernobyl and Fukushima (Patel, Larson, and Harvey 2022).

Today, the electricity system is undergoing another major transition, characterized by an increased emphasis on reduction of greenhouse gas emissions and climate change mitigation. Currently, electricity production is a major source of CO_2 emissions. According to the International Energy Agency (IEA), global CO_2 emissions from energy and industrial processes in 2022 stood at 36.8 Gt, with 14.6 Gt originating from power production (IEA 2022a). To limit global warming by 2 °C above the preindustrial level, the IEA estimates that by 2050, nearly 95% of electricity would come from low-carbon sources (IEA 2017).

Despite being a significant source of emissions, the electricity sector holds the potential to cost-effectively reduce emissions (Williams et al. 2012; IRENA 2022). Renewable energy sources like wind and solar are increasingly being adopted thanks to technology advancements and supportive policy incentives, leading to their growing share in the global energy mix (IEA 2022c; IRENA 2022).

2.2 Energy System Models and Agent-based Modeling

Computational models are commonly employed by scholars to address research questions about future electricity systems. Several review studies affirm the widespread use of models in probing future low-carbon electricity systems (see e.g. Bazmi and Zahedi 2011; Pfenninger, Hawkes, and Keirstead 2014; Tao et al. 2021). Computational models also serve as crucial tools for policy makers seeking to make informed decisions. For instance, the European Commission utilized the PRIMES (PRice-Induced Market Equilibrium System) model for its Energy Roadmap 2050 (European Commission 2011). The MARKAL (MARKet ALlocation) model has been influential in molding the UK's energy and climate policy (Taylor et al. 2014). The TIMES (Integrated MARKAL-EFOM1 System) model has been employed to support the formulation of national climate policy, as demonstrated in the case of Sweden (Krook-Riekkola 2016). Similarly, the U.S. Energy Information Administration has developed the NEMS (National Energy Modeling System) model for generating its Annual Energy Outlook (EIA 2023).

Prior research offers multiple paradigms for modeling energy system transitions, including optimization models, system dynamics models, and agent-based models (ABMs). Each paradigm offers unique strengths and capabilities, and may be better suited to particular kinds of problems. Here, we briefly summarize these three modeling approaches and elucidate our rationale for selecting ABM for this research.

Optimization models, as mathematical tools, seek optimal solutions within predefined parameters and constraints. An optimization model incorporates an objective function (to be maximized or minimized), and decision variables, and typically also has constraints that demarcate feasible solutions. Some well-known energy system optimization models include the above-mentioned MARKAL/TIMES (Loulou, Goldstein, and Noble 2004; Loulou et al. 2005), as well as PyPSA (Python for Power System Analysis) (Brown, Horsch, and Schlachtberger 2018), and OSeMOSYS (Open Source Energy Modeling System) (Howells et al. 2011; Niet et al. 2021). While optimization models excel at solving linear or convex problems, they fall short in simulating individual decision making with imperfect rationality, adaptive responses, feedback mechanisms, and emergent phenomena.

System dynamics models, on the other hand, are simulation techniques adept at analyzing complex dynamical systems. Comprising stocks, flows, and determinants of these flows, these models leverage feedback loops and time delays to examine system behaviors over time (Barbrook-Johnson and Penn 2022). They articulate the dynamic interactions among multiple system components, which can manifest as reinforcing or balancing feedback loops. From a mathematical standpoint, such a model is represented by a system of differential equations (Borshchev and Filippov 2004). Within the energy system modeling domain, applications of these models can be found in studies by Ahmad et al. (2015); Pereira and Saraiva (2011); and Yu et al. (2020). While potent for studying feedback mechanisms, the system dynamics model predominantly focuses on aggregate system dynamics, thereby offering limited insight into individual behaviors and heterogeneity among individuals (Borshchev and Filippov 2004; Köhler et al. 2018).

In contrast with the aforementioned modeling approaches, ABMs enable the simulation of individual entities' actions (decision making) and interactions. Agent-Based modeling is a simulation method commonly used to study complex systems composed of individual entities or "agents." These agents are autonomous and adaptive, governed by their decision-making processes and rules (Bonabeau 2002). Classic examples of ABMs include Schelling's segregation model (Schelling 1971) and the Sugarscape model (Epstein and Axtell 1996). ABMs have also been employed in recent studies to model phenomena such as infectious disease transmission, as evidenced by studies like Chang et al. (2020); and Rockett et al. (2020).

In our research, we perceive the low-carbon transition as an emergent outcome resulting from individual agents' actions and interactions, especially concerning investment decisions and their interaction with the electricity market. For an effective simulation of these elements, our chosen modeling tool must encapsulate individual actions while capturing heterogeneous and adaptive behaviors, alongside the path-dependency of the transition. Given its alignment with these requirements, ABM stands out as the appropriate tool for our purposes.

Even though ABMs are less commonly applied in energy system models than traditional energy-economy modeling techniques (Fernandez-Blanco-Carramolino et al. 2017), more and more studies have effectively used ABMs to study the transition of the electricity system (as will be demonstrated in the forthcoming paragraphs), highlighting their potential to incorporate diverse aspects for which traditional energy-economy models are less suited.

Various studies have utilized ABMs to model investment decisions in the power sector and their consequent impacts on the development of the overall electricity system. These models take into account investors' heterogeneity and adaptability, and the intricate interplay between the individual investors and the overall market. For instance, Botterud et al. (2007) simulated investment decisions of power generators in Korea, with agents employing the decision trees method to account for different scenarios in terms of load growth, hydropower conditions, and competitors' investment plans. Chappin et al. (2017) introduced the model EMLab (Energy Modelling Laboratory), a long-term agent-based modeling framework, to assess the effects of different policy instruments and market designs on investments in power generating capacity. This model accounts for investors' different asset portfolios and varying interest rates and forecasting horizons, while capturing the evolution of the electricity system over time. Safarzyńska et al. (2017) examined the feedback dynamics among the energy, technology, and financial sectors. Their model analyzes the interactions among consumers, electricity producers, power plants, and banking institutions within interconnected networks. This study further investigated the implications of energy policies on investment levels in renewable energy, as well as their influence on interbank connectivity and the potential for bank failures. Chen et al. (2018), studied power companies with heterogeneous risk profiles and technology preferences, analyzing their individual investment choices and their effect on the low-carbon transition of the electricity system in China. In another study, Kraan, Kramer, and Nikolic (2018) modeled investors with diverse expectations about the future, requiring different returns on capital and therefore using different discount rates for evaluating future cash flows. They found that incorporating heterogeneous investor behavior results in a large range of possible transition pathways within the power sector. Moreover, Fraunholz, Keles, and Fichtner (2019) applied an ABM called PowerACE to study generation and storage expansion planning in interconnected electricity markets. They used Nash-equilibrium to determine investment decisions and found that capacity remuneration mechanisms and cross-border effects influence investment incentives. Jonson et al. (2020) conducted an examination of a stylized electricity system under the influence of a progressively growing carbon tax. Within their model, agents are power companies making investments in new capacities. These agents project the potential profitability of various investment alternatives. The study subsequently contrasted these findings with results from a corresponding optimization model. Finally, Barazza and Strachan (2021) examined how historical path-dependency and imitation of successful investment behavior affect investments in electricity generation in the UK, Germany, and Italy. Their findings indicate that historical path-dependency reinforces the position of incumbent companies, while imitation promotes the diffusion of PV and entry of new actors into the electricity market.

To summarize, as highlighted in the aforementioned existing literature, ABMs are well-suited for studying the emergent behavior of a system (e.g., energy transitions) by modeling the behavior and interactions of individual agents (e.g., investors, producers, and consumers on the electricity market). In addition, agent-based models are suited for capturing the heterogeneity and complexity of decision-making processes among individual agents (e.g., different investors have different preferences regarding risks and technology choices). ABM can also represent the learning and adaptation processes of the agents (e.g., investors adapt their investment strategies according to market conditions).

However, the application of ABMs also comes with noteworthy challenges. Primarily, ABMs require modeling behavior at the individual level, demanding comprehensive data on agent behaviors and interactions. Unfortunately, such granular, individual-level data is often scarce. The lack of accurate data can pose challenges in constructing a representative model.

Moreover, the inherent complexity of ABMs, accentuated by the often unpredictable nature of agent behavior, can make the models challenging to validate (Windrum, Fagiolo, and Moneta 2007). The limitations specific to this thesis will be further explored in sections 3.3 and 4.7. The subsequent sections

2.3 to 2.5 will provide background information about the investigated parameters and variables.

2.3 Hurdle Rate

A hurdle rate is the minimum rate of return on an investment required by an investor (Kenton 2023). It plays a pivotal role in discounted cash flow analysis, used by investors to determine the net present value (NPV) or for comparisons with the investment's internal rate of return (IRR) (IPF 2017). As such, the hurdle rate is instrumental for assessing the economic viability of an investment and deciding whether to pursue a project.

In the real world, factors such as the weighted average cost of capital (WACC), perceived risk, target return, and historical performance are taken into consideration when determining a project's hurdle rate (IPF 2017). However, reliable data on actual hurdle rates and WACCs are often confidential and hence, not readily available to researchers. Various methods have been used to estimate the cost of capital, such as deriving data from financial markets, modeling auction results, consulting industry experts, and eliciting private party input (Steffen 2020).

A report from Europe Economics (2020) estimated that in the UK in 2018, hurdle rates were 5% for solar PV, 5.2% for onshore wind, 7.5% for combined-cycle gas turbines (CCGT), and 7.4% for coal plants with retrofit technologies. A survey conducted in 2019 across the US and Europe discovered that institutional investors' hurdle rates ranged from 10% to 11% for solar and wind, and 16% to 40% for new coal mines (Fattouh, Rahmatallah, and West 2019). According to a NERA (2015) study, UK nuclear hurdle rates fluctuated between 9.7% and 13.6% in 2015 and were projected to vary from 10.5% to 17.4% in 2030. The IEA (2022b) presented the WACCs for various technologies across countries. In Brazil, for instance, the WACC for solar PV varied between 7.3% and 15.1% in 2019 and 6.6% to 18% in 2021. Meanwhile, in South Africa, the WACC ranged from 6.6% to 17.1% in 2019 and shifted to 5.8% to 18.1% in 2021. It's worth noting that these data indicate considerable variability in hurdle rates across different countries, technologies, investors, and timeframes.

García-Gusano et al. (2016) demonstrated the significant impact of the choice of discount rate[2] on the selection of technology for investment in energy optimization models. This thesis, particularly in Paper I and Paper IV, examines the influence of the hurdle rate's value on investment decisions in an ABM setting. In addition, in contrast to many model studies, these two papers also seek to capture the heterogeneity and the dynamic nature of hurdle rates and analyze how the choice of hurdle rate impacts investment decisions.

2.4 Uncertainties, Risk Aversion and Loss Aversion

According to the classic distinction between uncertainty and risk by economist Frank Knight, uncertainty refers to situations in which the outcomes are not known, and the probabilities of these outcomes are not known and cannot be estimated, whereas risk refers to situations in which the possible outcomes and the probabilities of these outcomes are known or can be estimated (Knight 1921).

In the field of economics, risk aversion describes a preference for a guaranteed outcome over a risky choice with an equivalent expected outcome (Werner 2016). One commonly used framework to model behavior under risk is the Expected Utility Theory (EUT), attributed to Daniel Bernoulli in the 18th

[2] In finance, the terms "discount rate" and "hurdle rate" are often used in different contexts, however, when the hurdle rate is used as the discount rate in an NPV calculation, then it is effectively serving the same role as a discount rate.

century (Bernoulli 1954). EUT assumes that individuals are risk averse and make decisions to maximize a concave utility function. However, the theory has faced criticism for its reliance on assumptions that may not always align with real-world features. An alternative model, Prospect Theory, was proposed by psychologists Kahneman and Tversky (1979), to better describe how people actually make decisions under risk and uncertainty. Prospect Theory posits that individuals weigh the potential value of losses more than equivalent gains, introducing the concept of loss aversion. In contrast to the uniform concave utility function of EUT, Prospect Theory employs a utility function that is convex for losses and concave for gains.

In many cases, probability distributions are not known, and decision makers may form "subjective probability distributions" (Johansson-Stenman 2011; Savage 1954). Unlike objective probabilities, which are based on empirical data or a well-defined random process such as a coin toss, subjective probabilities are typically based on personal judgment, intuition, or belief.

Investment in the energy sector is replete with uncertainties and risks, such as technological, economic, and regulatory factors. Higher levels of uncertainty and risk will likely increase the perceived subjective risk, significantly influencing decision-making processes, especially for risk- and/or loss-averse individuals. Uncertainties and risk, coupled with investors' risk and loss aversion, have a profound influence on shaping risk perceptions, expected returns, and financing costs associated with low-carbon technology investments. Consequently, these factors play an instrumental role in determining the success of the transition toward a low-carbon electricity system.

Despite its profound significance, there is a noticeable gap in the literature regarding the integration of uncertainty and risk and aversion to it into agent-based energy system models. Only a handful of studies have adopted methodologies such as EUT (see e.g. Anwar et al. 2022) and Prospect Theory (see e.g. Tao, Moncada, and Delarue 2023).

In this thesis, specifically in Papers III and IV, we explore these concepts by integrating the element of investment decisions under uncertainty, coupled with investors' risk and/or loss aversion. Paper III presents results using three distinctive approaches for modeling risk or loss aversion where the investors have subjective probability distributions for future carbon prices. The three approaches are (1) the mean-variance approach; (2) the Value-at-Risk (VaR) approach; and (3) the risk-adjusted discount rate approach.

The mean-variance approach (or the modern portfolio theory) is an investment or portfolio selection method that takes into consideration both the expected returns and the associated variances of those returns for investment assets. This dual focus allows investors to optimize their portfolios for maximum return while minimizing risk. Within this framework, an investor may opt for a portfolio that offers a higher anticipated return for a specified level of risk, measured as variance, or, alternatively, may select a portfolio with minimized variance for a specified level of expected return (Bodie, Kane, and Marcus 2010). The mean-variance approach can be derived from the expected utility approach, where the utility function can be approximated by using mathematical techniques such as Taylor expansion (Pulley 1981). Based on this approximation, it can be shown that there is a trade-off between the expected return and the variance of the return.

Value at Risk (VAR) is a risk-management metric often used in financial applications. Functioning as a statistical measure of prospective losses, VaR offers an estimate of the worst-case scenario for a given investment portfolio. More formally, VaR quantifies the worst loss over a target horizon that will not be exceeded with a given level of confidence (Jorion 2007). Investors might demand different VaR limits depending on their individual loss-aversion levels.

The risk-adjusted discount rate approach posits that the greater the perceived risk, the higher the discount rate demanded by investors, implying that a more substantial expected return is necessitated by these investors (Lewellen 1977).

2.5 Learning and Adaptation

Learning can be characterized as “the activity of obtaining knowledge”, while adaptation refers to “the process of changing to suit different conditions”(Cambridge Dictionary 2023a, 2023b).

Learning and adaptation are fundamental behaviors observed in biological and social systems, acting as the drivers of evolution and progress. From viruses to humans in complex societies, those entities that demonstrate the greatest aptitude for learning and adapting to their environments are most likely to succeed. This concept is encapsulated by Charles Darwin's principle of 'Survival of the Fittest,' which suggests that the most adaptable are the most likely to thrive.

The fundamental behaviors of learning and adaptation have transformative implications, not only in natural systems. In the study of artificial systems in computer science, an instance is reinforcement learning, a branch of machine learning where an agent learns to make optimal decisions by performing actions that maximize cumulative rewards in an environment (Sutton and Barto 2018). Prominent applications of reinforcement learning are seen in projects like AlphaGo, which mastered the intricate board game Go and outperformed human champions (Silver et al. 2016). Similarly, Generative Pre-trained Transformer (GPT) models like ChatGPT employ reinforcement learning techniques to generate human-like text (Brown et al. 2020). These models demonstrate the immense potential of integrating learning and adaptation in artificial systems, allowing solutions to complex problems as well as decision-making capabilities that, in some areas, surpass human skills.

In the evolving realm of energy systems, learning and adaptation are fundamental. Agents like investors, energy providers, consumers, and policymakers continuously interact with their environment and each other. They learn from past experiences and adapt their behaviors and strategies in response to system changes, such as fluctuating energy prices, geopolitical shifts, and advancements in technology. Incorporating learning and adaptation at the agent level in energy system models could provide a more detailed representation of system complexities and potentially lead to significant contributions. Some previous studies have demonstrated this application, cf. Perera and Kamalaruban (2021); and Zhang, Zhang, and Qiu (2020).

In this thesis, specifically in Paper IV, we introduce a rudimentary learning and adaptation behavior into the HAPPI model. We examine how learning and adaptive behavior regarding the hurdle rate influences investors' decision processes concerning investments in new generation capacity.

3. Method – The HAPPI Model

The HAPPI (Heterogenous Agent-based Power Plant Investment) model is used across all papers. The model is developed throughout these investigations, but its core structure remains consistent. The core model, derived from Jonson et al.'s (2020) study, forms the structural underpinning of this research. The model versions utilized in Papers I and II were implemented in Mathematica, while the models for Papers III and IV were developed in Python. The code for the models, made accessible under open-source provisions, can be found at https://github.com/happiABM.

The following sections first provide an introduction to the core model in Paper I and then proceed to elaborate on its development through each of the succeeding papers.

3.1 Core Model Structure – the Model Used in Paper I

The overarching structure of the HAPPI model is visually depicted in Figure 2. It comprises power companies, as well as the electricity system and consumers.

The power companies are referred to as 'agents' within this context. The agents, who invest, own, and operate power plants, seek to invest in technology with the highest profitability. They decide on both investments and power generation.

The electricity system component simulates an ideal market, where neither producers nor consumers make strategic bids to manipulate the market price. A power plant generates electricity as long as the electricity price is greater than or equal to its operating cost.

The consumer component of the model simulates the electricity demand.

Electricity prices are set by where the demand equals supply, and they are influenced by several factors, including the installed capacity of electricity supply technologies, fuel costs, wind and solar conditions, as well as electricity demand. Additionally, this model simulates the dispatching of electricity production and computes both the CO_2 emissions and revenues for each power plant.

In a feedback loop, the agents and the electricity system exert mutual influence. The investment decisions made by the agents impact various aspects of the electricity system, such as the generation supply mix, CO_2 emissions, and electricity prices. The market conditions change over time and, in turn, shape the agents' future investment choices.

The scheduling of the model, as illustrated in Fig.3, is structured such that at the commencement of each year, power plants that have reached their operational lifespan are decommissioned one by one; simultaneously, the agents, in randomly assigned turns, evaluate investment options and make informed investment decisions. There are six potential technologies: coal-fired plants, gas combined-cycle plants (GCC), GCC with Carbon Capture and Storage (GCC with CCS)[3], nuclear plants, wind, and solar photovoltaics (PV). Each agent, for each potential investment option, calculates a profitability index and invests in the technology yielding the highest expected profitability index. Should no technology present a positive profitability index, the agent opts out of investing during that round. This decision-making process continues until no more power plants are to be decommissioned in that year and no agents want to invest further. Subsequently, the model advances to the next year, and the whole scheduling process is repeated.

[3] Gas combined cycle with CCS (gas CCS) is included in Paper I and Paper II, but not in Paper III and Paper IV. While drafting Paper III in 2021, the authors felt that the rapidly evolving landscape of renewable energy technologies and climate policy warranted a focused exploration of a fossil-fuel-free energy system. Given this aim, and to streamline our analysis in this direction, we decided to exclude gas CCS from the current version of the model.

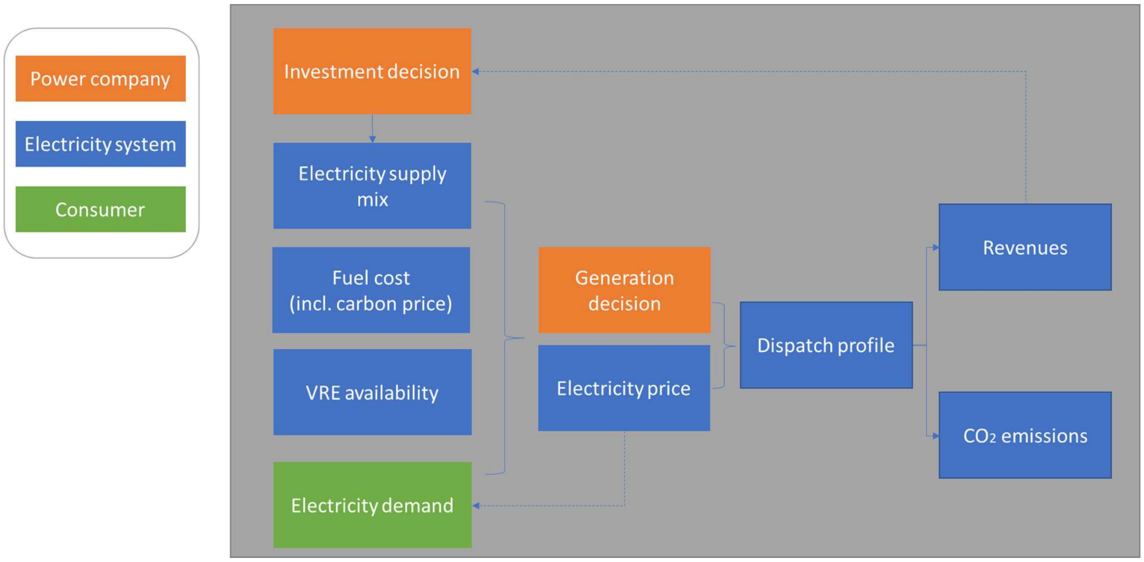


Figure 2. The overarching structure of the HAPPI model. This model can be mainly divided into two parts – the agents (the investors) part, and the environment (the electricity system) part.

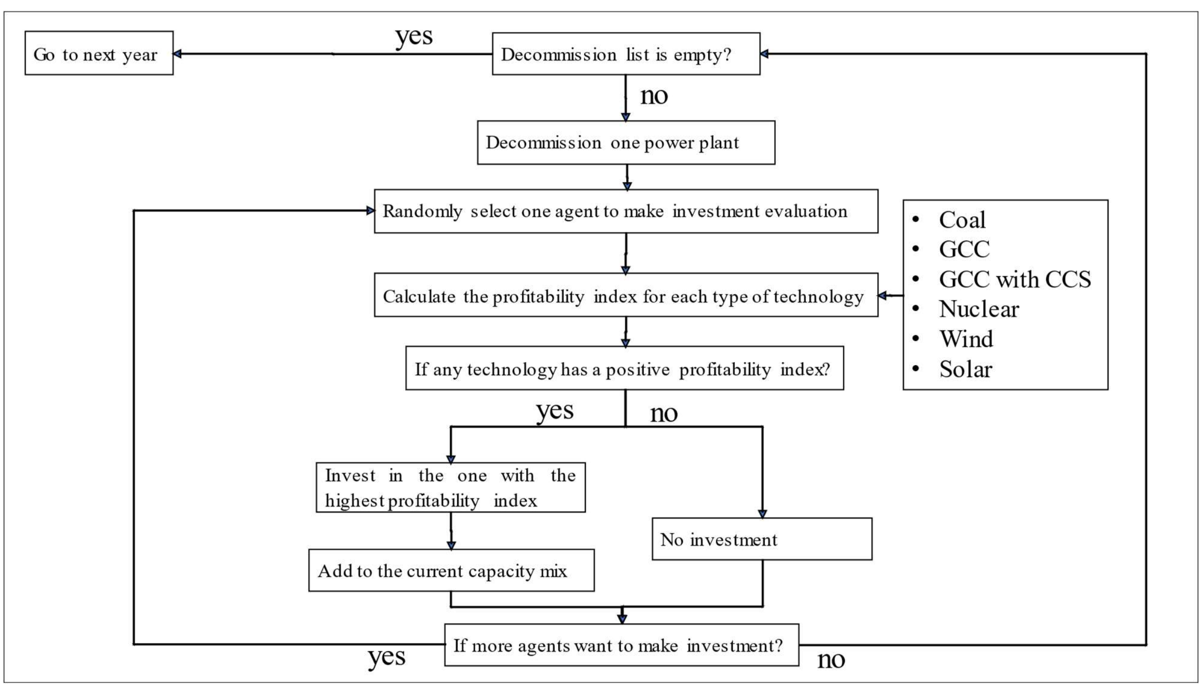


Figure 3. The overarching scheduling of the HAPPI model. At the beginning of each year, power plants that have reached their operational lifespan are decommissioned. Concurrently, agents assess investment opportunities and make new investment decisions. Agents will invest in the technology that offers the highest expected profitability index, as long as it is larger than zero.

Profitability index calculation

The profitability index of investing in a power plant of technology *T*, denoted as π_T, is derived from the Net Present Value (*NPV*) of the potential investment, adjusted by the capital cost of the technology, denoted as I_T, and by the Capital Recovery Factor (*CRF*) of this technology CRF_T. It is expressed as follows:

$$\pi_T = \frac{NPV}{I_T} \times CRF_T \tag{1}$$

$$NPV = \sum_{t=1}^{L_T} \frac{r_t - c_t}{(1+\gamma_t^T)^t} - I_T \tag{2}$$

$$CRF_T = \frac{\gamma_t^T}{1-(1+\gamma_t^T)^{-L_T}} \tag{3}$$

In these equations:

- r_t is the annual revenue generated by selling electricity from the plant at year *t*.
- c_t is the operating cost for the plant at year *t*.
- γ_t^T is the hurdle rate of technology T at the year *t*.
- L_T is the lifespan of the plant for technology *T*.

To estimate the revenue, an agent runs an internal electricity market simulation. First, the agent incorporates a hypothetical power plant of the type under consideration into the current capacity mix. To estimate the future generation capacity mix, the agent assumes the system capacity mix over the lifetime of the hypothetical plant will mirror the current situation. Fuel costs for coal, natural gas, biogas, and nuclear fuel are considered constant in this study (Paper I). A carbon price is also factored into operational costs for fossil fuel-based plants. In our model, we assume a rising carbon price scenario.

Agents then run the internal electricity market simulation to estimate the lifetime revenue from this hypothetical plant. This process is further detailed in the following section.

The Electricity Market Simulation

The model assumes power plants dispatch electricity according to the merit order. The demand curve follows an iso-elastic demand function (Eq. 4), determining the electricity produced and consumed q_τ in time slice τ and the corresponding electricity price p_τ.

$$q_\tau = q_{0,\tau} \times \left(\frac{p_\tau}{p_0}\right)^\epsilon \tag{4}$$

In this equation:

- $\varepsilon = -0.05$ is the elasticity.
- $q_{0,\tau}$ is the reference demand, which reflects the varying demand over the different time slices over a year and gives the demand for electricity when the price of electricity equals the reference level p_0. The reference demand $q_{0,\tau}$ is chosen so that the time slices correspond to the varying electricity demand in Germany in 2011, with $p_0 = 3.25$ €ct/kWh, following Jonson et al. (2020).

To address the variability of variable renewable energy (VRE) and electricity demand in a year, we use 64 representative time slices τ. Both the reference demand and the availability of VRE (i.e., the condition of wind and solar) are constant for each time slice throughout the simulation, and agents have full information about these values.

Armed with information about electricity supply, demand, and operational costs, agents can simulate the electricity market. This enables them to calculate the electricity price for each time slice over the course of a year and estimate the revenue from the hypothetical plant currently under evaluation. The final investment decision is made based on the expected profitability index of each option. Once an investment is made, this information becomes public, and is taken into account by all agents when assessing potential subsequent investments. The newly invested power plant commences electricity production in the following year.

This 'Electricity Market Simulation' process is also utilized in the model for actual electricity market simulation, determining the electricity dispatch and establishing electricity prices.

3.2 Model Development in Papers II, III, and IV

Paper II – Financial Feedback and Stochasticity

Paper II introduces two extensions to the original model described above: the inclusion of a financial module and the integration of stochastic elements.

In contrast to Paper I, where it is assumed that agents can always secure loans for investments, Paper II introduces a financial module that monitors each agent's financial status. This status determines an agent's capacity to undertake future investments. The mechanism operates as follows:

An agent is required to finance a fraction, denoted as f, of any new investment from its own bank account, i.e., savings; the remaining fraction, denoted as $(1-f)$, is financed through a bank loan, i.e., debt, that incurs interest.

Profits generated from the agent's plant operations, through the sale of electricity, accumulate in the agent's account, and a portion, denoted as f_{div}, of the capital is paid to shareholders as a dividend d, given that planned investments for the forthcoming years can be made. The agent's equity E is assumed to be the estimated value of its plants (V) plus the bank account holdings M minus the debt D to the bank ($E = M + V - D$). If an agent's equity falls below zero, the agent is declared bankrupt and is disallowed from making further investments. For a comprehensive description of the financial module, please refer to Paper II.

The second modification to the model in Paper II is the incorporation of time-varying stochastic parameters, x_t , generated through a first-order autoregressive model approach (AR1). The value of a parameter in the succeeding year, x_{t+1}, is dependent on its value in the current year, x_t.

$$x_{t+1} = x_t + \varepsilon_1(\bar{x} - x_t) + \varepsilon_2 \cdot z_{t+1} \tag{5}$$

Where $\bar{x}$ is the long-term average value of the parameter x_t, and ε_1 and ε_2 are parameters of the stochastic process. Stochasticity comes from z_{t+1}, a real-valued random number drawn from a uniform distribution ranging from -1 to +1. The process is mean-reverting (or stationary) if $\varepsilon_1 < 0$.

Paper II primarily investigates three stochastic parameters: gas price, coal price, and electricity demand.

Paper III – Uncertainty, Risk Aversion, and the Portfolio Approach

Paper III extends the core model (Paper I) by integrating uncertainty and risk and loss aversion into the agent's investment decision-making process. Additionally, this study refines the computation of the profitability index. Instead of evaluating the profitability of each technology in isolation, the updated approach assesses the impact that investing in a specific technology has on an agent's overall portfolio profits.

The main uncertainty explored in this study pertains to future carbon prices. This uncertainty impacts the expected profits of various technologies, thereby influencing agents' investment choices.

Agents, while aware of historical carbon prices, remain uncertain about future values. They use their subjective probability distribution to predict potential future carbon prices. They base their predictions on average carbon price over the past five years, with future carbon prices assumed to follow a discrete uniform distribution:

$$[\bar{p}^{CO2}_{future}] = \bar{p}^{CO2}_{past} \times [\omega - 3\Delta_{CO_2}, \omega - 2\Delta_{CO_2}, \omega - \Delta_{CO_2}, \omega, \omega + \Delta_{CO_2}, \omega + 2\Delta_{CO_2}, \omega + 3\Delta_{CO_2}] \quad (6)$$

- $\bar{p}^{CO2}_{future}$ denotes a set of possible future carbon prices that the agent expects. Each value represents an average future price level rather than a specific year.
- $\bar{p}^{CO2}_{past}$ denotes the past five-year average carbon price.
- ω is the median value of the discrete uniform distribution.
- Δ_{CO_2} signifies the spread in the carbon price.

To study risk and loss aversion, we have implemented and compared three distinct modeling approaches, as detailed in section 2.4: (1) the Value-at-Risk (VaR) approach; (2) the mean-variance approach; and (3) the risk-adjusted discount rate approach. Below, we provide a brief overview of how these three approaches are explored in Paper III. For more detailed information about the implementation, please see section 2.2.3 in Paper III.

(1) Value-at-Risk (VaR) approach

When using the VaR approach, the agent not only evaluates the expected profitability but also the probability that an investment may result in losses. In the context of this study, an agent evaluates the profits of investing in a particular technology under seven different scenarios of carbon prices as indicated in Eq. 6. After this evaluation, the agent then counts the number of scenarios where the profits are positive. For the agent to even consider investing, this count must exceed or equal a certain threshold set by the agent, denoted by λ. We have tested different λ values in Paper III. A higher λ value, i.e., a higher required probability that the investment generates positive profits, means a higher aversion to losses.

(2) Mean-variance approach

The mean-variance approach evaluates investments by considering both the expected profits and the variance of those profits, stemming from uncertainty in carbon prices. A parameter "γ" is used to represent an agent's aversion level to variance. A higher γ value indicates that an agent is more sensitive to variations in potential profits. Conversely, a lower γ suggests that the company is more tolerant of potential profit fluctuations. We have tested different γ values in Paper III.

(3) Risk-adjusted discount rate approach

In the context of Paper III, 'hurdle rate' is used to represent the risk-adjusted discount rate when calculating the NPV and CRF. For analysis in Paper III, a uniform hurdle rate is employed to discount the future revenues for the agent's entire portfolio. We've tested different values for the risk-adjusted discount rate. A higher discount rate used by the agent corresponds to an agent with a higher degree of risk and loss aversion.

Paper IV – The Adaptive Approach

Paper IV enhances the model from Paper II by making it possible for agents to adaptively respond to evolving investment conditions. The model also accommodates the agents' diverse loss-aversion levels, thereby allowing heterogeneity in their adaptive responses.

The model allows agents to dynamically adjust their individual hurdle rates for each technology on an annual basis. These adjustments consider both the historical economic performance of the specific technology and the agent's individual aversion to financial losses. The hurdle rate adaptation for a specific technology depends on two key indicators. The first is the average ex-post profitability at year t generated by technology T over the past N years, denoted by $\bar{C}_t^T$. For a specific technology type, the ex-post profitability in a particular year is calculated by subtracting the operating cost and the annuitized capital cost of a plant from its annual revenue. The second indicator, denoted by m_t^T, measures the frequency of negative ex-post profitability (or losses) associated with technology T over the preceding N years. Each technology's hurdle rate is then adjusted based on whether $\bar{C}_t^T$ and m_t^T meet an agent's own threshold values. In general, if a technology has had a history of underperformance, indicated by $\bar{C}_t^T < 0$, and its count of negative profitability m_t^T exceeds the agent's loss-averse threshold λ, its hurdle rate will be increased. Conversely, if $\bar{C}_t^T \geq 0$, and m_t^T is below or equal to the agent's loss-averse threshold λ, the hurdle rate for that technology will be lowered. Please refer to section 2.1 in Paper IV for a detailed description of how this was implemented in the model.

3.3 Reflections on Model Choices and Assumptions

Modeling investment decisions concerning low-carbon transitions requires making a variety of assumptions, including but not limited to investors' evaluation criteria, future fuel and carbon prices, and technology advancements. In this section, we delve into some key choices and assumptions made during the modeling process and explain their rationale. We do not address all choices and assumptions exhaustively, focusing on those deemed significant to our research and pertaining to queries frequently made by peers.

3.3.1 Investment Evaluation Criteria

In terms of evaluation criteria, our model—like many energy models—presumes that investors primarily aim for profit maximization. We focus on simulating the investment decisions of power companies, adopting the assumption of profit-driven investors, as we assume that their owners primarily aim for financial gain. However, it is important to note the diverse array of investors in the energy sector. Beyond power companies, this includes municipalities, states, homeowners, farmers, and more. These investors' motives, backgrounds, resources, and personal characteristics vary, and they may not universally be driven by profit (Bergek, Mignon, and Sundberg 2013; Langniss 1996). We recognize the rising number of other investor types in the energy sector, particularly within renewable energy technologies. We recommend that future studies address the diverse motives of different investor types. But as a first approximation, it may be reasonable to assume that most large-scale companies that dominate the electricity sector are primarily driven by the goal of maximizing profits.

Another essential consideration when it comes to deciding which investment criteria to choose is whether to utilize a portfolio approach, in which an investment is considered within the investor's entire portfolio, or a standalone approach, which evaluates each investment independently. Each approach has its advantages and limitations, with the standalone approach offering simplicity and clarity in understanding specific investments' risks and returns, while the portfolio approach acknowledges the effects of diversification, potentially reducing the overall risk of the investor's portfolio.

In our research, we've primarily adopted the standalone approach (used in Papers I, II and IV). According to our model's framework, an investment should be pursued if it’s individually profitable (accounting for risk-mitigation measures), even if it may appear unprofitable within the broader portfolio context. This rationale stems from the idea that if other investors seize these profitable opportunities, this can influence market dynamics and potentially result in financial losses for this investor in both standalone and portfolio perspectives. Nevertheless, acknowledging the prevalent use of the portfolio approach in economic literature (see e.g. Awerbuch and Berger 2003; Tietjen, Pahle, and Fuss 2016), we have employed it in one of our studies (Paper III).

3.3.2 Forecasting Future Values

Investment decisions for power plants require investors to forecast future conditions in the energy system, such as future capacity mix, fuel prices, electricity demand, energy policies, taxes, etc. For accurate forecasting, it's preferable to use sophisticated models and methodologies, which can for example include the application of artificial intelligence (Ahmed and Khalid 2019).

However, due to the expensive nature of such forecasting and the limitations of this project, we made pragmatic decisions about modeling agents' predictions of future electricity system conditions as described in section 3.1. Future work could include more sophisticated forecasting methodologies in the model. Still, in reality, it should be kept in mind that no matter how advanced the forecasting methods are, there will remain a lot of uncertainty about future conditions, in particular over the long term. Thus, investments in the electricity system will always have to be made under such (difficult) conditions.

3.3.3 Generation Technologies

The selection of generation technologies incorporated into our model—specifically, coal, gas combined cycle (with and without CCS), nuclear, wind, and solar—was chosen to provide a comprehensive representation of the energy mix. Each technology embodies various aspects of the energy system: coal and nuclear for baseload generation, gas for flexible generation, and wind and solar for intermittent renewable generation. This selection allows the model to capture a diverse range of dynamics within the electricity market.

Nevertheless, several technologies such as battery storage, hydro power, and coal with CCS were excluded to maintain simplicity, while still capturing a core of the energy mix. Battery storage, although crucial for technologies like wind and solar, would add significant complexity.[4] Hydropower is excluded from our study primarily because we focus on modeling the transition to a future electricity system in a setting that resembles a country with limited potential for hydropower, such as Germany. Coal with CCS, largely resembles nuclear power in the context of our model, in the sense that it has a high capital cost, low running cost, and low CO_2 emissions. Thus, for the sake of simplicity, it has been omitted.

The absence of these technologies is not meant to suggest that they lack potential significance or relevance. Instead, these choices were made based on the specific objectives and constraints of our study, with the aim to balance complexity, comprehensibility, and the model's intent to capture the main dynamics of electricity systems. Future development of the model could consider incorporating these additional technologies, depending on the research questions posed.

[4] Initial attempts were made to incorporate battery technologies into our model. However, the complexities introduced by these technologies led us to deviate from this path to maintain the focus and simplicity of our model.

3.3.4 Additional Concerns/Assumptions

Other factors, while not included in our model, are important to consider. These factors—including but not limited to land use, leap time, and technology learning[5]—were excluded to maintain manageability and clarity in our model. Their relevance notwithstanding, incorporating them would complicate the model and potentially dilute its core messages and the insights obtained. The exclusion of these elements is a limitation and a trade-off made to balance realism, usefulness, and complexity. Future work could attempt to incorporate these aspects, given sufficient resources and time.

[5] In 2021, we explored the incorporation of endogenous technology learning into our model and conducted preliminary testing. However, due to scheduling conflicts with other research projects, we did not continue to pursue this.

4. Results and Discussion

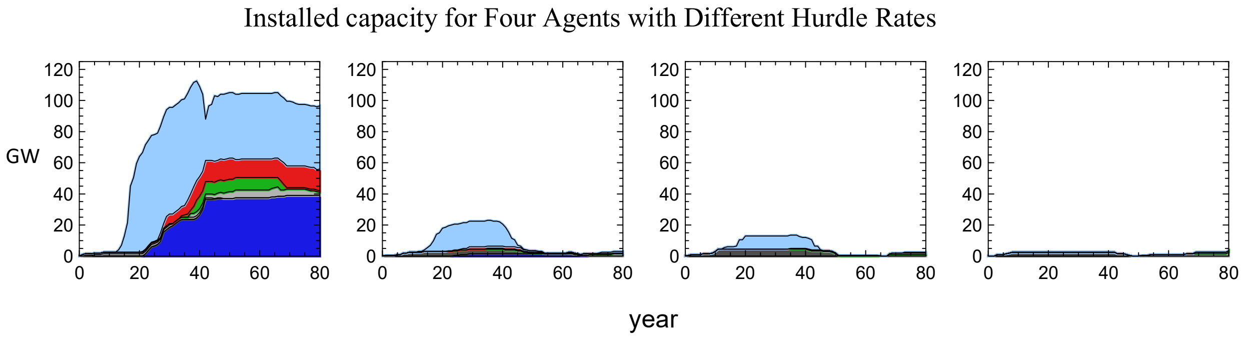
This thesis, as discussed in preceding sections, primarily investigates the influence of five key factors on investor decision making and their subsequent impacts on the low-carbon transition of the electricity system. Specifically, we have examined: (1) hurdle rates, (2) expectations on future carbon prices, (3) access to capital, (4) risk and loss aversion, and (5) learning and adaptation. This section presents some of the key findings and sheds light on the implications of these factors, both for the individual agents and at systemic levels.

4.1 Hurdle Rate

The influence and implications of hurdle rates on investment decisions were analyzed in Paper I and Paper IV.

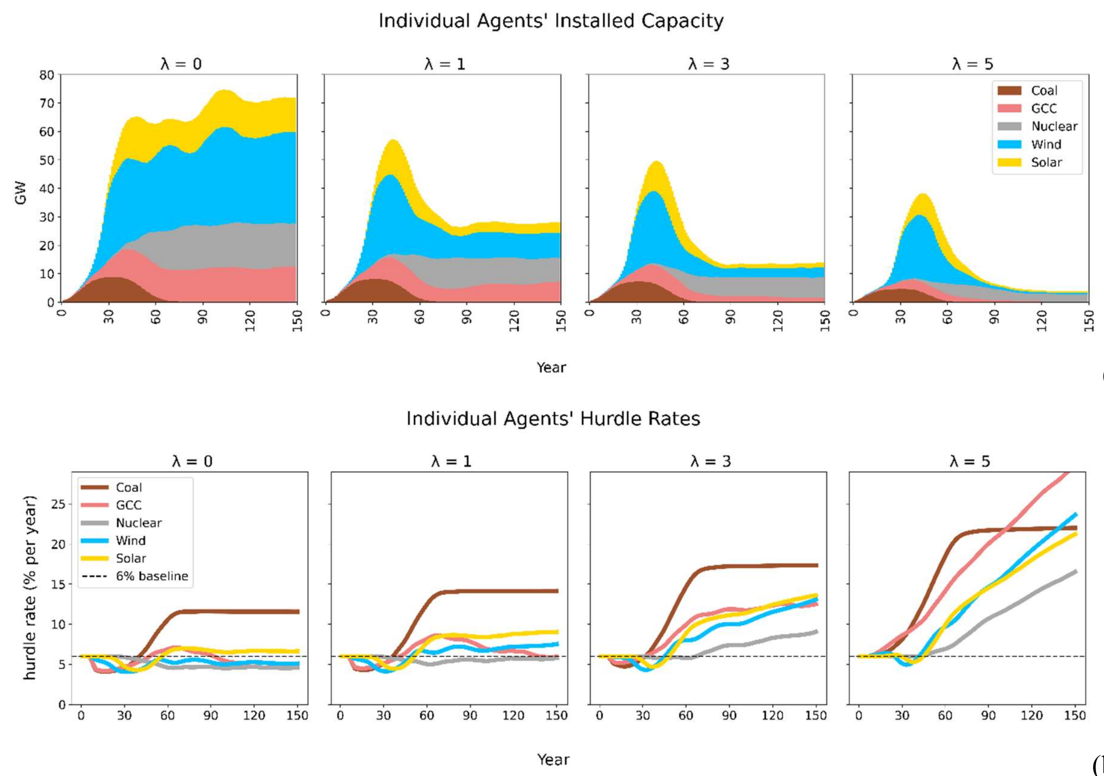
One scenario, presented in Paper I, involves 25 agents, each applying a unique hurdle rate ranging from 5% to 11% per year (with increments of 0.25%), denoted as $r = [5\%, 5.25\%..., 10.75\%, 11\%]$. In this scenario, each agent's hurdle rate remains unchanged throughout the duration of the study, and is identical across all technologies. In Paper IV, we model the adaptive hurdle rate of agents. In this scenario, there are four representative agents. Initially, they adopt a standard hurdle rate of 6% per year, which they adjust over time based on the historical performance of various technology options and the agents' individual loss-aversion levels.

Despite differences in the model settings between the two papers, both consistently reveal that agents with lower hurdle rates tend to invest more, as depicted in Figures 4 and 5. This trend can be explained by the fact that agents with lower hurdle rates require lower returns and therefore have an increased propensity to invest. As investment activity increases, it exerts downward pressure on electricity prices, which in turn reduces the profitability of agents maintaining higher hurdle rates and demanding higher returns.



(a) (b) (c) (d)

Figure 4. Results from Paper I illustrate the installed capacity for agents with differing hurdle rates. (a) r=5.0%/year, (b) r=5.25%/year, (c) r=5.5%/year, (d) r=5.75%/year. The agent with r= 5%/year dominates in terms of investing, while agents with r>6.75% make no investments.



(a)

(b)

Figure 5. Results from Paper IV illustrating (a) Installed capacity per agent; and (b) the progression of individual agents' hurdle rates over time. λ represents an agent's loss-aversion level: a larger λ indicates greater loss aversion. (The coal hurdle rate remains constant after approximately year 60 due to the absence of coal plants in the system, which results in a lack of data for adjusting the hurdle rate.) The figure shows the average outcome from 1000 simulation runs.

At a system level, findings from Paper I suggest that lower hurdle rates adopted by agents could potentially facilitate an earlier transition towards a low-carbon electricity system (Figure 6). This is because lower hurdle rates reduce the levelized costs of wind and nuclear energy more than they do for coal, hence leading to an earlier introduction of wind and nuclear options as compared to scenarios where agents employ higher hurdle rates.

Our research highlights that reducing risk, which lowers hurdle rates, could act as a strategy for accelerating the transition towards a low-carbon future. This insight underscores the potential of financial and regulatory policies in motivating investors to adopt lower hurdle rates. For example, policymakers could implement low-interest loans, guarantees, or subsidies to mitigate the perceived financial risks associated with low-carbon technology investments (IEA 2008; Kalamova, Kaminker, and Johnstone 2011; Ming et al. 2014). By leveraging these strategies, we could stimulate more significant investment in low-carbon technologies and expedite the transition to a low-carbon electricity system.

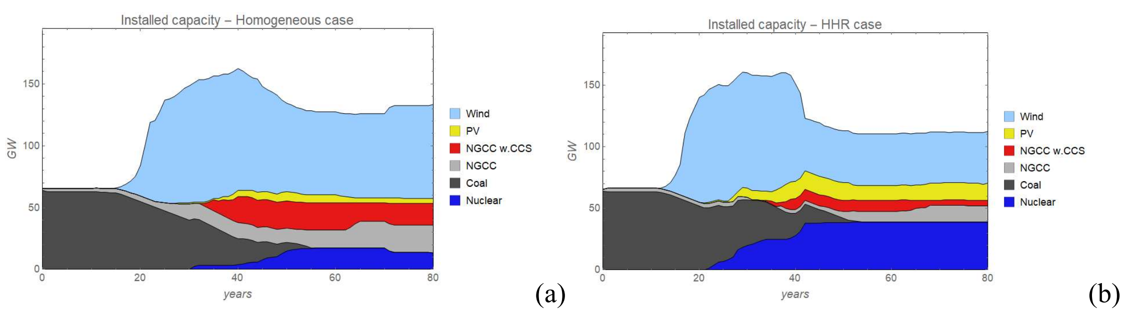


Figure 6. The system installed capacity over 80 years in the (a) homogeneous case where all agents use an 8%/year hurdle rate, and (b) Heterogeneous hurdle rate (HHR) case. There are 25 agents, each applying a distinct hurdle rate that ranges from 5% to 11% per year, increasing in increments of 0.25%. 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 HHR case than in the homogeneous case.

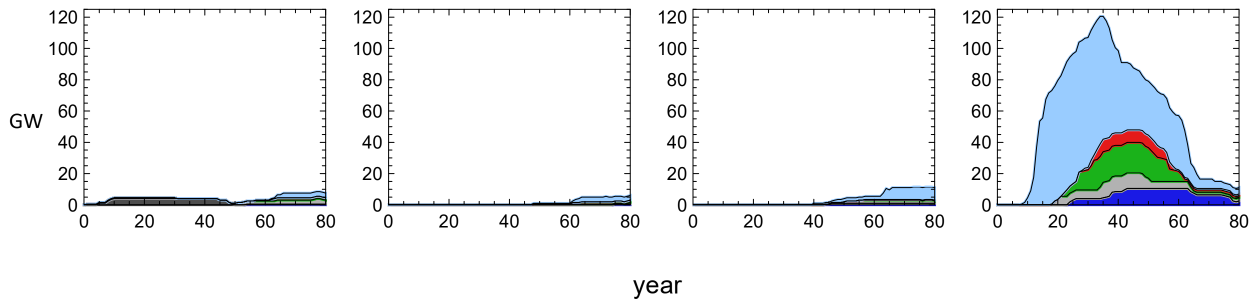
4.2 Expectations of Future Carbon Prices

Papers I and III explore the influence of agents' expectations of future carbon prices on their investment decisions. In our model, we assume a rising carbon price scenario that is zero during the first 10 years, after which it grows linearly to 100 €/ton CO_2 in year 50 and then stays constant at that level.

One scenario presented in Paper I involves 16 agents who each anticipate a different rate of carbon price growth, denoted by the coefficient β. This value ranges uniformly from 0 to 1.5, with increments of 0.1. These agents only know the exact carbon price for the next year. They forecast the carbon price level a decade ahead and assume that the price remains stable thereafter. In this scenario, agents using a β value less than 1 underestimate the growth, those employing $\beta = 1$ predict the true carbon price level in ten years, while agents adopting a β greater than 1 overestimate the carbon price.

Under the growing carbon price scenario, Paper I shows an earlier transition from a fossil-based to a low-carbon system when agents anticipate higher future carbon prices. Furthermore, as illustrated in Figure 7, in a situation where each agent expects a different future carbon price trajectory, the agent with the highest expected carbon price predominates in investing as the higher carbon price yields higher expected electricity prices and hence higher profits from investments. Once this agent (see case d in Fig.7) invests, these investments will outcompete investments from the other actors who believe in lower future carbon prices.

Installed Capacity for Four Agents with Different Carbon Price Expectations



(a) (b) (c) (d)

Figure 7. Installed capacity of selected agents among the 16 discussed in Paper I. Each agent is characterized by a different coefficient β. (a) β =0.0, (b) β =1.0, (c) β =1.2, (d) β =1.5. The agent with β =1.5 dominates the investing for the first 50 years; after this, all agents contribute to new capacity.

In Paper III, we continue to explore agents' expectations of future carbon prices by investigating the impact of the perceived uncertainty in future carbon prices, expressed as ΔCO_2 (as demonstrated in Eq.6). In this context, agents have a subjective distribution regarding future carbon prices. A smaller ΔCO_2 value indicates that agents expect a narrower range of potential future carbon prices, indicating a lower degree of perceived uncertainty. Conversely, a larger ΔCO_2 value suggests that agents anticipate a wider range of future carbon prices, implying higher perceived uncertainty.

Findings from Paper III suggest that if a risk- or loss-averse agent expects low uncertainties in carbon prices, investments in low-carbon technology generally commence sooner and in larger volumes, as shown in Figure 8. Conversely, if these agents anticipate high uncertainty in future carbon price levels, investments in low-carbon technologies will be deferred, and the total volume of investments will decrease. Instead, they invest more heavily in gas-fired power plants, leading to increased electricity prices. Higher uncertainty in carbon price also leads to higher total CO_2 emissions, as shown in Fig. 9.

Together, investigations from Papers I and III underscore that both higher expectations of future carbon prices and lower perceived uncertainty in these prices can expedite the transition to a low-carbon electricity system. These results carry implications for policymaking and market signals. Policymakers can shape investors' expectations about future carbon prices by creating and communicating clear, credible, and consistent policies. Efforts to reduce the uncertainty surrounding future carbon prices can also play a significant role. This could be achieved through transparent, long-term policy planning, and consistent implementation, which reduces the volatility of carbon pricing and gives investors greater confidence in the stability of their returns.

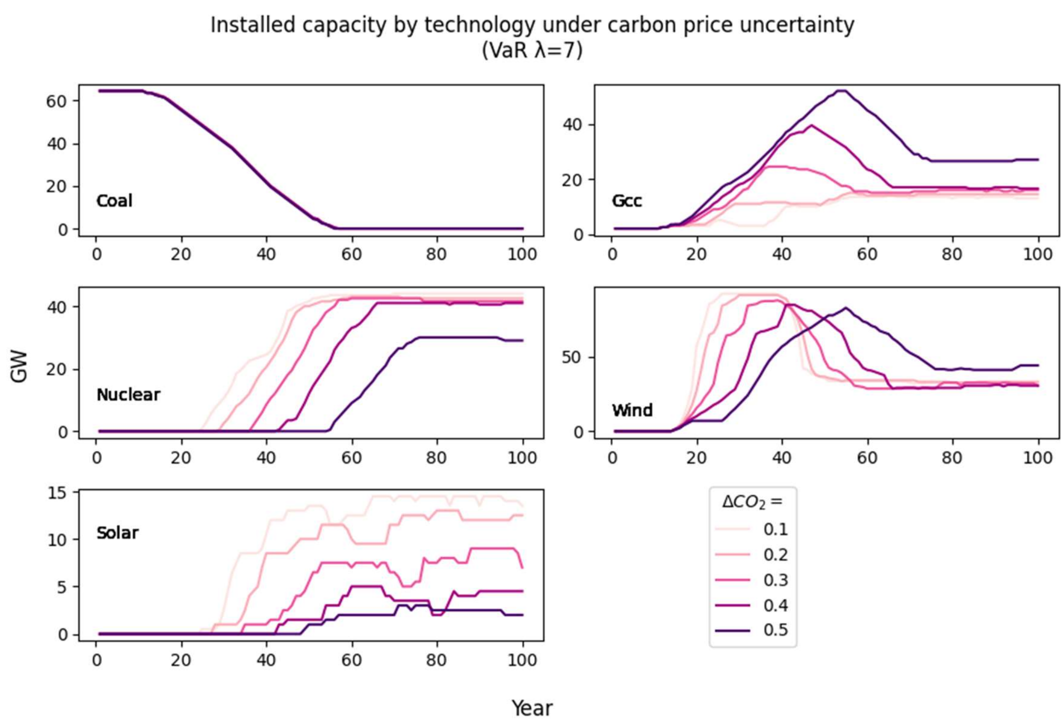


Figure 8. Installed capacity of each technology under different levels of carbon price uncertainty, modeled using the Value-at-Risk (VaR) approach. With this method, agents count instances of positive profits from seven possible carbon price scenarios. An investment is considered by a company only if the number of positive instances meets or exceeds the threshold number, λ. When the uncertainty level is higher (a larger ΔCO_2), we observe a further delay in investments in low-carbon technologies and more investments in GCC.

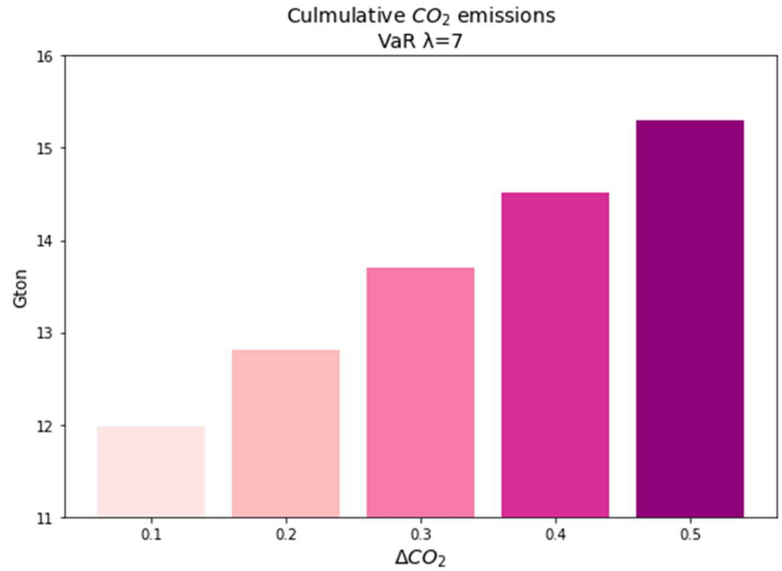


Figure 9. Cumulative CO_2 emissions over a 100-year simulation period under varying levels of carbon price uncertainty, modeled using the Value-at-Risk (VaR) approach. The uncertainty level is denoted by ΔCO_2; a higher ΔCO_2 indicates greater uncertainty. Notably, increased carbon price uncertainty positively correlates with elevated cumulative CO_2 emissions.

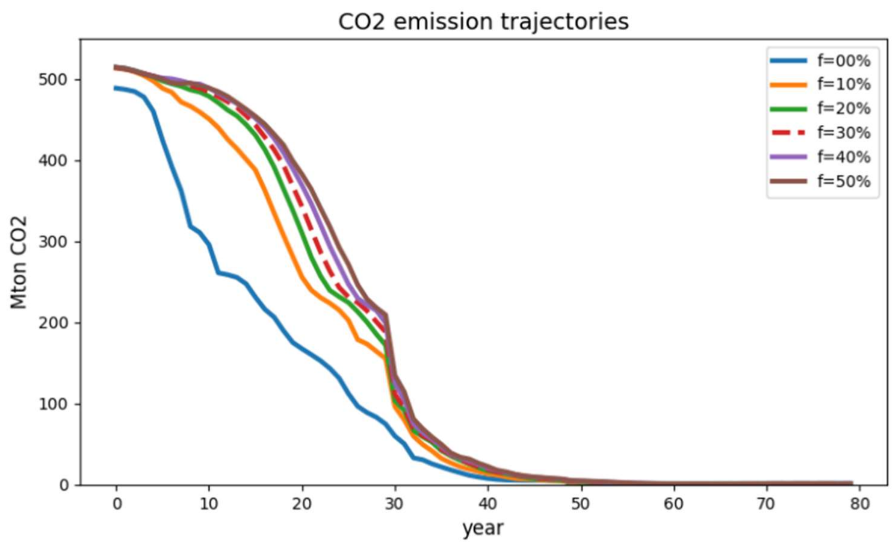
4.3 Access to Capital

Paper II focuses on understanding the impact of capital accessibility on investors' decision-making processes related to power plant investments, as well as on the speed of the low-carbon transition. Access to capital is characterized by two key parameters in Paper II:

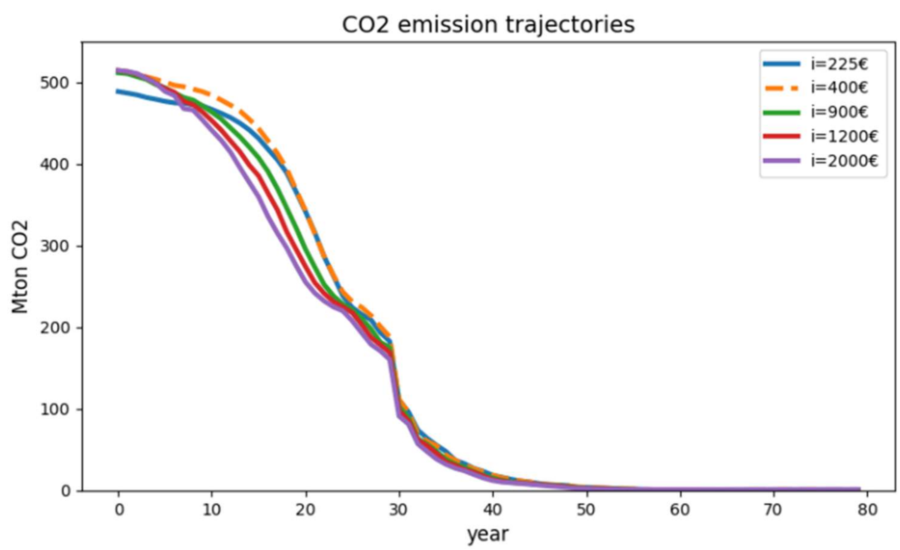
- f : The fraction of an investment that is required to be financed by an agent's own bank account. A larger value indicates less access to external capital, whereas a lower value suggests greater access to external capital.
- i : The initial capital (in million euros) in an agent's bank account. A larger value indicates greater internal capital availability at the outset.

We conducted two sets of tests varying the levels of f ($f \in \{0\%, 10\%, 20\%, 30\%, 40\%, 50\%\}$) and $i(i \in \{225, 400, 900, 1200, 2000\})$, respectively. Our findings demonstrate that greater access to (either external or internal) capital, i.e., smaller f or larger i, leads to more rapid mitigation of CO_2 emissions (Fig.10). This is attributed to an increase in investments in capital-intensive, low-carbon technologies such as wind, nuclear, and photovoltaic (PV) power. In contrast, limited access to capital produces the reverse effect: capital constraints impede the expansion of low-carbon technologies and slow down the phasing out of coal-fired power plants (Fig. 11a). In addition, our analysis reveals that the influence of the financing proportion required by an agent's own capital (f) is more pronounced than that of the initial capital (i) parameter.

These findings highlight the critical role that access to capital plays in facilitating a successful transition toward a decarbonized electricity system. The implementation of low-carbon infrastructures requires substantial capital investment, underscoring the need for suitable policy measures to ensure sufficient capital availability for investors. Policymakers might consider financial instruments such as green bonds, low-interest loans, or subsidies. In addition, partnerships with private financial institutions and international financial organizations could be pursued to secure the necessary funding for the transition.

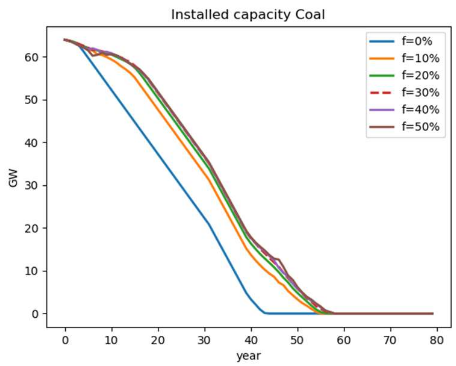


(a)

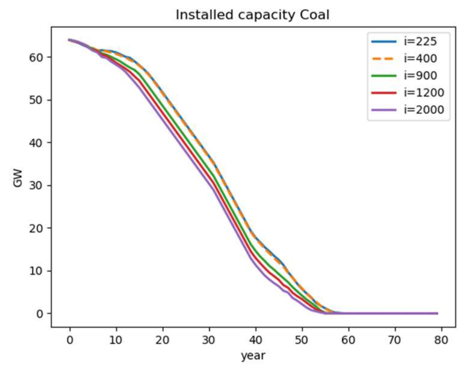


(b)

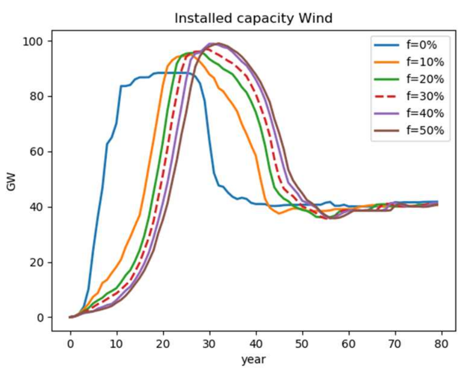
Figure 10. Comparison of emission reduction trajectories under two tests: (a) Varying the constraint factor $\boldsymbol{f}$ *while keeping the initial capital* $\boldsymbol{i}$ *constant at 400 million euros; (b) Altering* $\boldsymbol{i}$ *while holding* $\boldsymbol{f}$ *constant at 30%. Emissions decrease more rapidly when agents face fewer constraints and have greater access to capital.*


Installed capacity Coal
GW
year
f=0%
f=10%
f=20%
f=30%
f=40%
f=50%

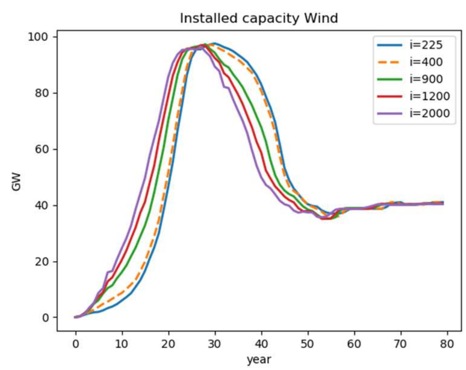
(a)


Installed capacity Coal
GW
year
i=225
i=400
i=900
i=1200
i=2000

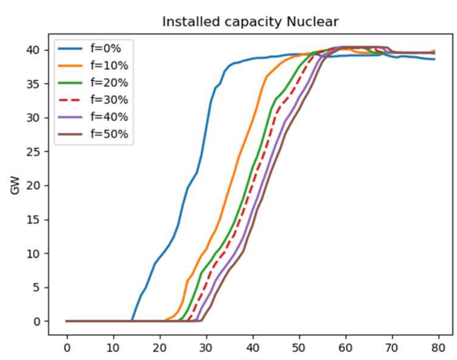
(b)


Installed capacity Wind
GW
year
f=0%
f=10%
f=20%
f=30%
f=40%
f=50%

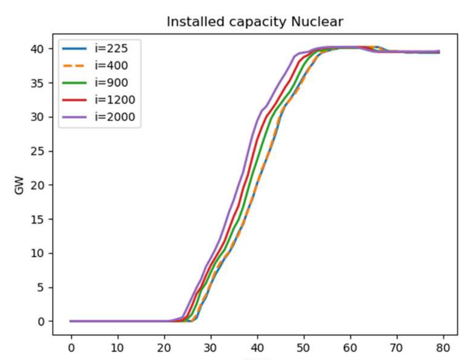
(c)


Installed capacity Wind
GW
year
i=225
i=400
i=900
i=1200
i=2000

(d)


Installed capacity Nuclear
GW
year
f=0%
f=10%
f=20%
f=30%
f=40%
f=50%

(e)


Installed capacity Nuclear
GW
year
i=225
i=400
i=900
i=1200
i=2000

(f)

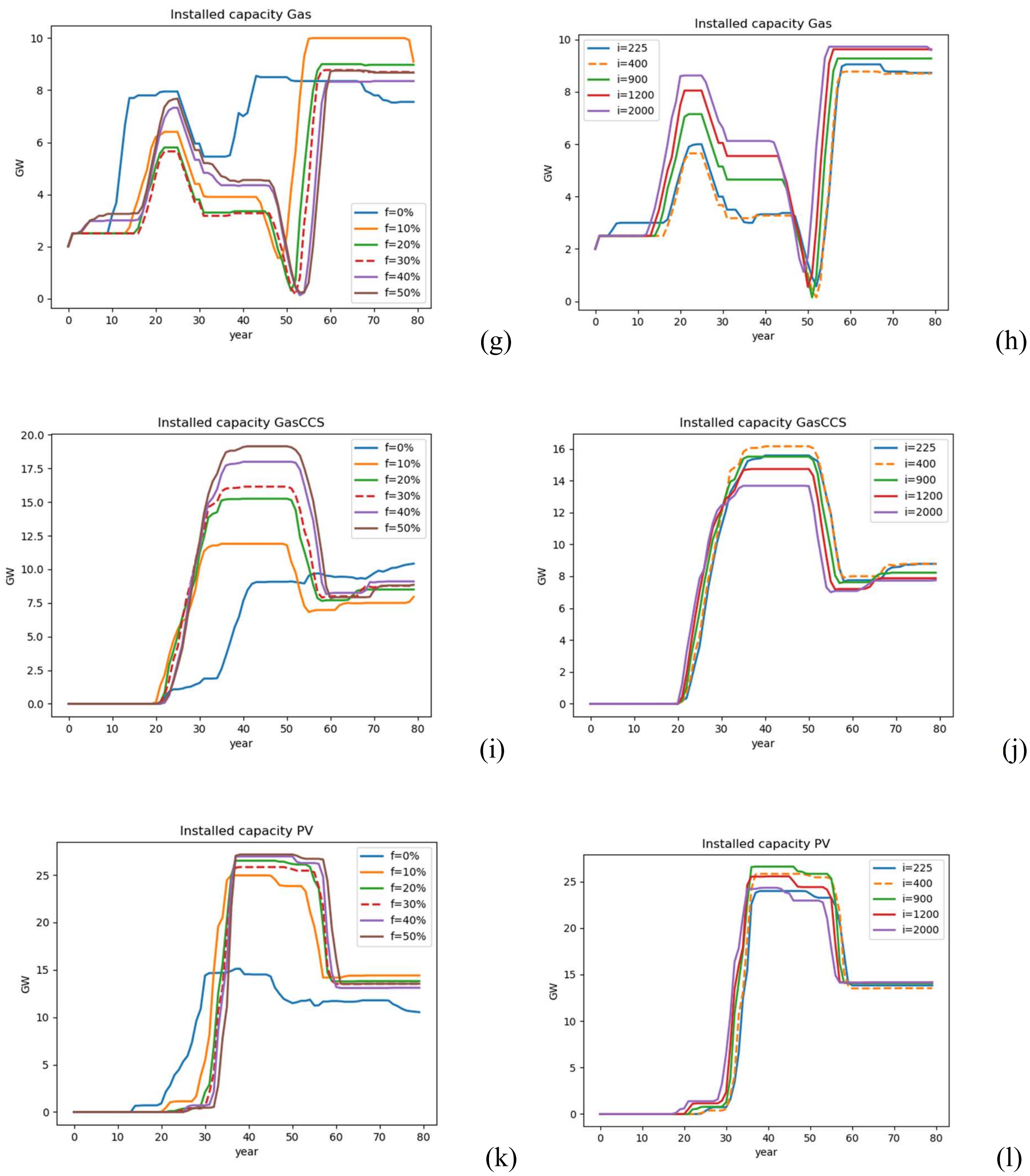


Figure 11. Comparative analysis of installed capacity across different technologies with varied access to capital. (a-b) coal; (c-d) wind; (e-f) nuclear; (g-h) gas; (i-j) gasCCS; (k-l) solar PV. ***f*** *is the fraction of an investment financed by an agent's own capital and* ***i*** *is the initial capital in an agent's bank account. In the left column of panels, we vary the self-financing fraction* ***f*** *while keeping the initial capital* ***i*** *constant at 400 million euros. In the right column of panels, we modify the initial capital* ***i*** *while holding* ***f*** *constant at 30%.*

4.4 Risk and Loss Aversion

In Paper III and Paper IV, we have analyzed how investors' risk and/or loss aversion behavior influences their investment decisions. In Paper III, we examine the investment decisions of risk-averse investors under carbon price uncertainty. This paper compares three distinct methods for modeling investors' risk and loss aversion – the Value at Risk (VaR) approach, the mean-variance approach, and the risk-adjusted discount rate. Paper IV delves into a scenario where agents adapt their hurdle rate according to both their own levels of loss aversion and the past economic performance of specific technologies.

Upon comparison of risk- or loss-averse agents with risk-neutral ones, our findings from Paper III reveal that risk or loss aversion, coupled with carbon price uncertainty (which causes agents to form subjective probability distributions about future carbon prices), generally delays the transition towards a low-carbon electricity system. The risk or loss-averse agents exhibit differences in the timing and volume of investments compared to risk-neutral agents. Furthermore, the introduction of risk and loss aversion together with uncertainty in carbon prices leads to a rise in electricity prices and an increase in cumulative CO_2 emissions (Figs. 12 and 13).

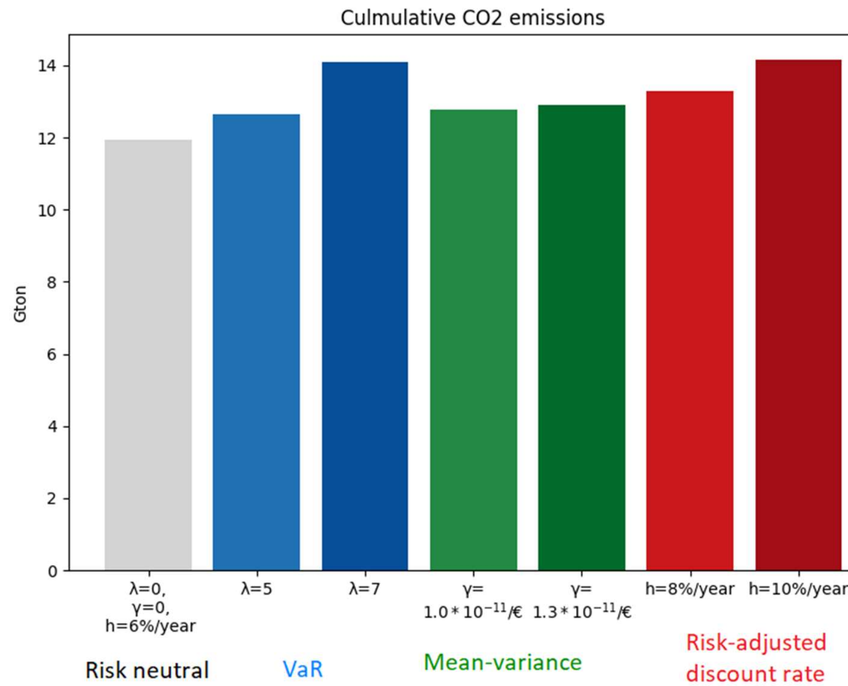


Figure 12. Cumulative CO_2 emissions over a 100-year simulation period for cases using different risk-aversion levels. The first column represents a risk-neutral scenario, while the subsequent six bars depict risk-averse scenarios. The blue bars employ the VaR approach; the green bars employ the mean-variance method; and the red bars are based on the risk-adjusted discount rate approach. The magnitude of the risk-aversion parameter (whether λ, γ, or h), denotes the level of risk aversion: a larger parameter indicates greater risk aversion. Notably, all three methods yield higher CO_2 emissions when a higher risk-aversion level is assumed.

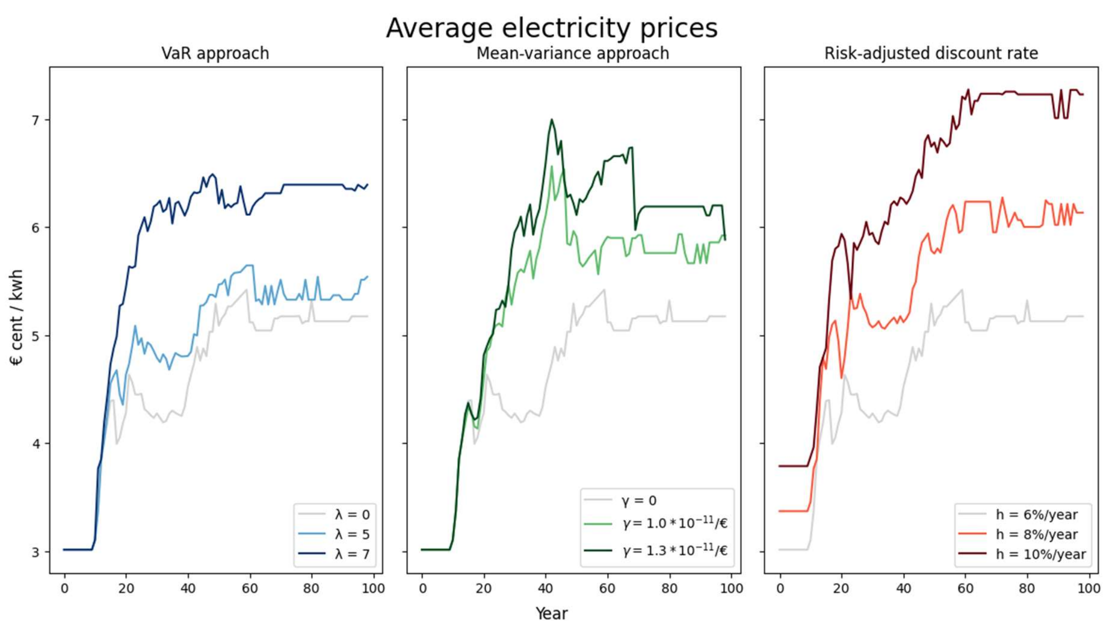
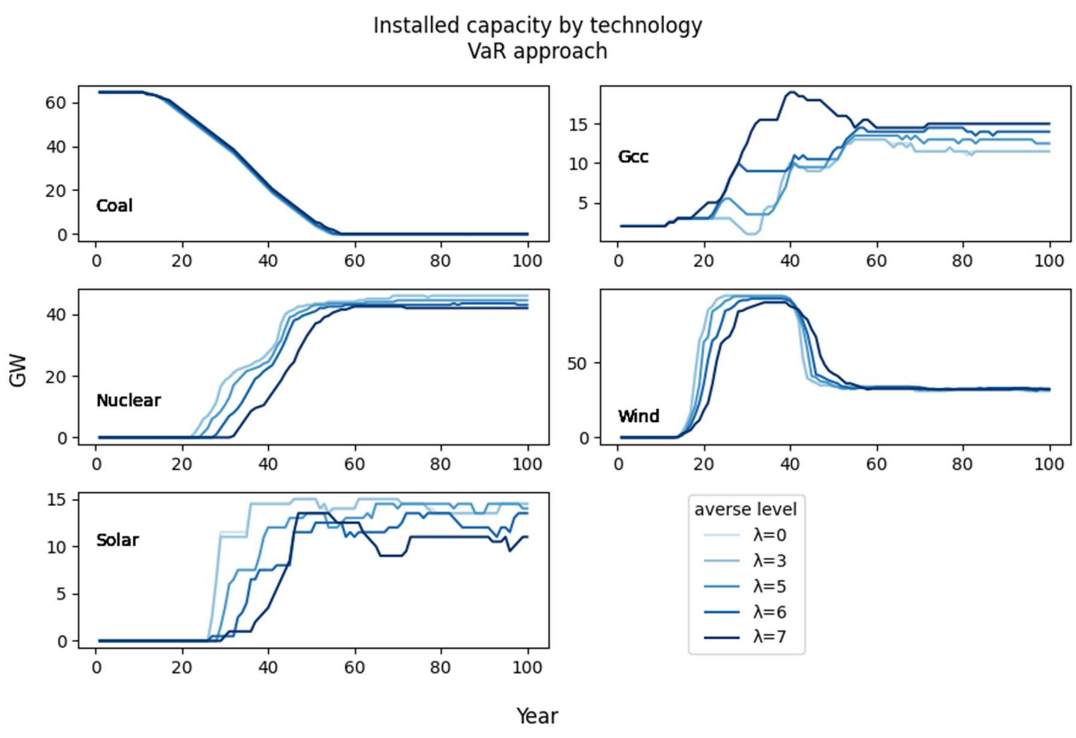
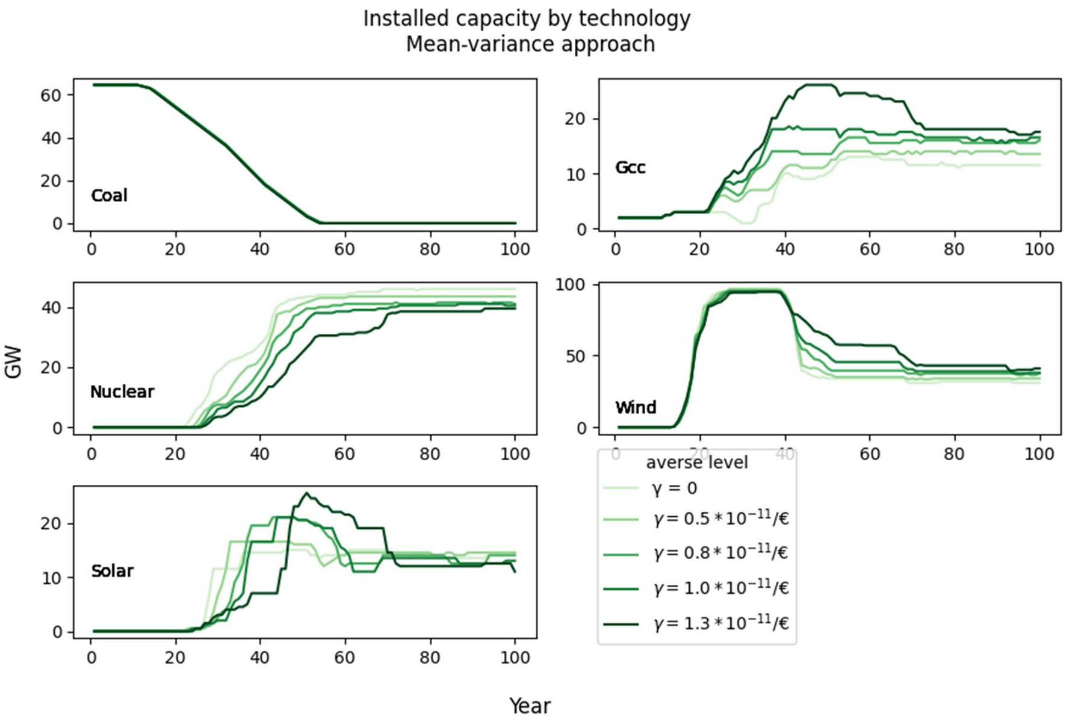


Figure 13. Average electricity prices over a 100-year simulation period. Three panels represent three distinct risk-aversion modeling approaches: VaR; Mean variance, and Risk-adjusted discount rate. The value of the risk-aversion parameter, be it λ, γ, or h, signifies the level of risk aversion, with a larger parameter indicating increased risk aversion. Notably, each method results in higher electricity prices as the assumed risk-aversion level rises.

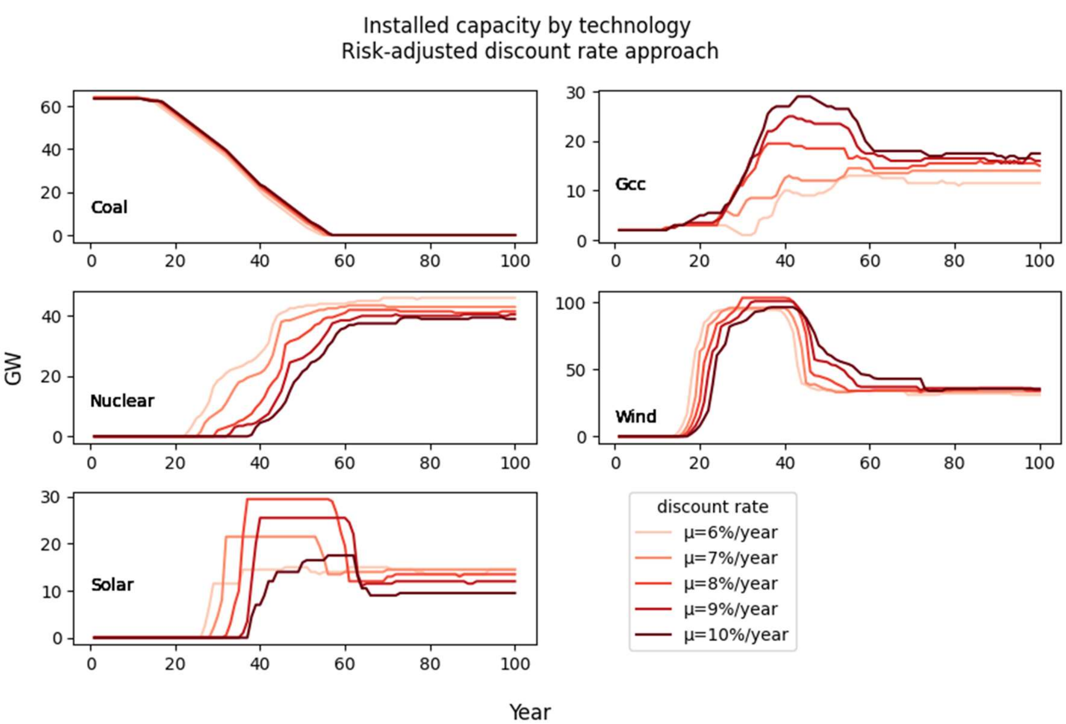
Upon implementing the three distinct approaches for modeling investor risk and loss aversion, we observe similar outcomes on the system level across the three methods, namely a delayed transition (Fig. 14). However, the underlying rationale for these delays and the specific mechanisms shaping technology investment preferences differed across the three models. The VaR approach assumes that investors focus on losses within the profit distribution, whereas the mean-variance approach assumes an aversion to uncertain returns. The risk-adjusted discount rate approach implies a higher hurdle rate and hence a lower willingness to invest in capital-intensive technologies.



(a)



(b)



(c)

Figure 14. System installed capacity of each technology over 100-year simulation time for different risk-aversion approaches: (a) VaR; (b) Mean variance; (c) Risk-adjusted discount rate. The risk-aversion parameter, be it λ, γ, or h, represents the level of risk or loss aversion: a larger parameter signifies heightened risk or loss aversion. For all three approaches, there is a noticeable delay in investments in low-carbon technologies, with more investments in GCC.

In Paper IV, we discover distinct investment patterns among agents with varying degrees of loss aversion. Specifically, we find that agents exhibiting a lower aversion to losses tend to invest more, whereas those displaying higher loss aversion tend to be more conservative in their investments (see Fig. 5a and Fig. 16b). Interestingly, agents who invest more frequently often accumulate higher equity, but they also exhibit greater susceptibility to bankruptcy since they are less averse to loss (see Fig. 15). This underscores the complex trade-off between risk and return in investment decision making.

Understanding investor behavior and decision making in the context of risk and loss aversion offers a more nuanced perspective on the electricity system's dynamics. These findings not only highlight the importance of considering risk and loss aversion when modeling investment decisions but also help identify potential challenges and opportunities during the transition towards a low-carbon energy system. As our findings highlight, risk- and loss-averse investors may slow down the expected pace of a transition due to their cautious investment approach. This underlines the critical role of policymakers and regulators in fostering an environment that minimizes controllable investment risk and incentivizes risk-averse entities to support low-carbon technologies. Moreover, our work highlights the potential risks of extensive investments for investors, which, despite leading to higher equity, lead to an increase in the likelihood of bankruptcy.

Our study also underscores the importance of researchers thoroughly comprehending the risk- and loss-aversion behavior of companies to select the most appropriate modeling method that aligns with their research objectives.

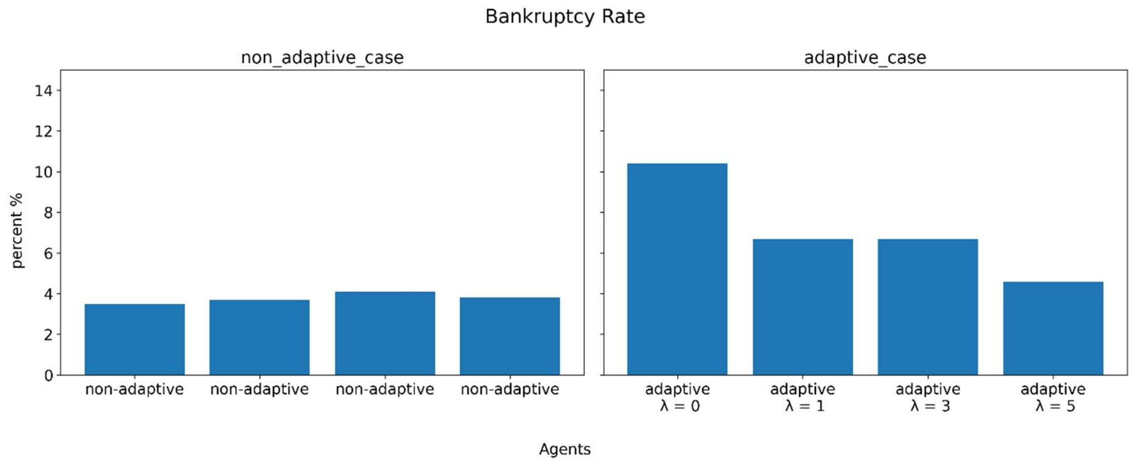


Figure 15. Bankruptcy rate for each agent. (Left) non-adaptive case; (Right) adaptive case. The results are based on 1000 simulation runs. In the left panel, all agents are identical and do not adapt their hurdle rates, but there is a random process that decides the order in which invest first, and therefore the outcome for the companies is somewhat different (despite them being equal). In the right panel, agents are heterogeneous and λ represents the agent's loss-averse level.

4.5 Learning and Adaptation

In Paper IV, agents adjust their hurdle rates each year based on two key factors: a technology's past five-year economic performance and the individual agent's level of loss aversion. A technology's economic performance is measured by an ex-post profitability index as explained in section 3.2. Should a technology's economic performance fail to meet the agent's economic performance requirement and loss-aversion threshold, the agent increases the hurdle rate for this technology by 0.5 percentage points to account for the heightened perceived risk. In contrast, if a technology surpasses the agent's requirement, the agent lowers its hurdle rate for that technology by 0.5 percentage points.

We examine two primary cases in Paper IV: one in which agents are non-adaptive, and another in which agents are adaptive and exhibit varying degrees of loss aversion. In both cases, we ran 1000 simulations to account for the stochastic fuel prices, carbon prices, and electricity demand. For a detailed description of our method, please refer to Paper IV.

Our results show the contrasting investment decisions between adaptive and non-adaptive investors (Fig. 16). Non-adaptive agents, due to their homogeneity, make identical investment decisions, whereas adaptive agents customize their investment decisions based on the past economic performance of various technologies and their own levels of loss aversion.

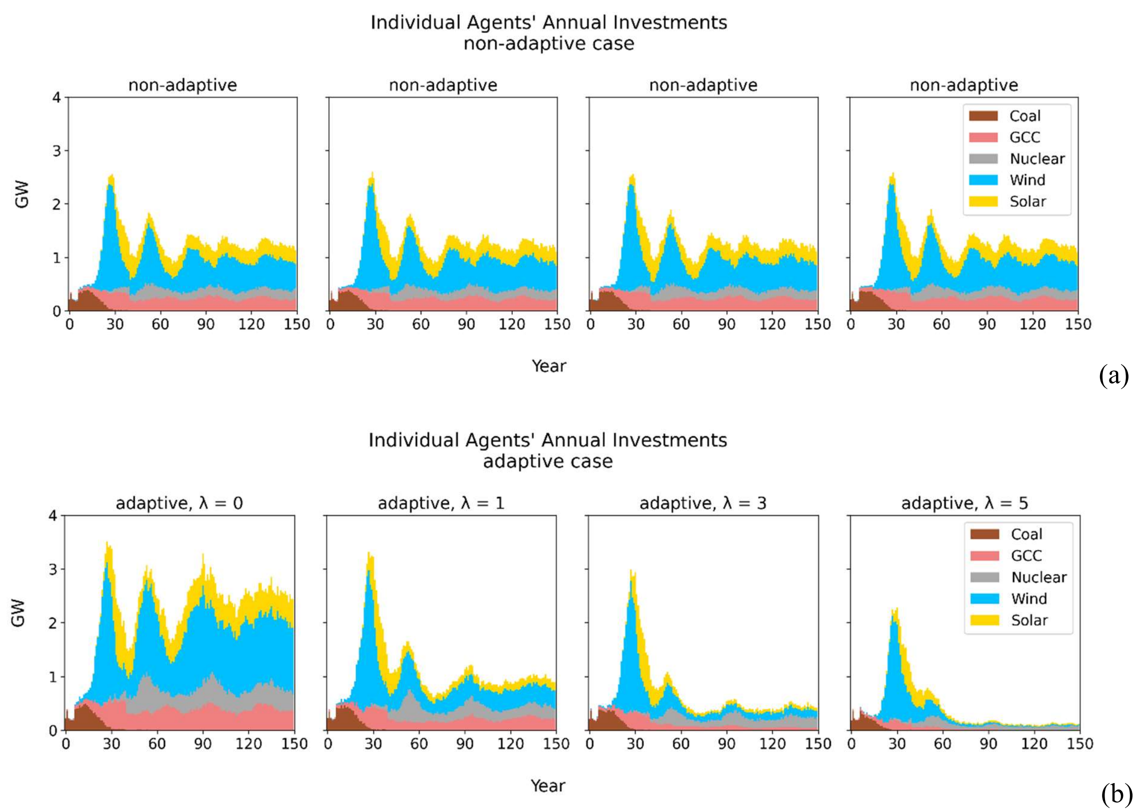


Figure 16. Annual investment by individual agents: Panel (a) represents the non-adaptive case, while Panel (b) shows the adaptive case. Non-adaptive agents, being homogeneous, make uniform investment decisions. In contrast, adaptive agents adjust their decisions according to the past economic performance of different technologies and their own levels of loss aversion.

Notable disparities are also observed at the system level. Fig.17 compares the installed system capacities in cases with non-adaptive and adaptive agents.

These differences can be observed during both the capacity expansion and post-expansion phases of wind and solar technologies, albeit with different directional tendencies. During the expansion phase (around year 20 to 50), agents invest more in wind and solar on average in the adaptive case, but, post-expansion, investments in these two technologies recede while investments in nuclear power rise when compared to the non-adaptive case. These observations emphasize the capacity of adaptive agents to adapt their investment decisions in response to the economic performance of diverse technologies.

Further, these two cases exhibit differences in the distribution of the installed capacities across various technologies over time. The distribution, represented by the 10th and 90th percentiles in Figure 17, arises from the stochastic processes for prices and electricity demand. The differences in the distribution between non-adaptive and adaptive cases (i.e., the range of the distribution of the installed capacity) become particularly pronounced for wind and solar after year 50. The adaptive case displays a broader range between the 10th and 90th percentile for wind and solar capacities. This suggests that the attractiveness of investing in solar and wind technologies is more sensitive to the realization of different stochastic processes and agents' adaptivity than other technologies.

The findings from our study underscore the value of integrating adaptive behaviors into future investment models, thereby reflecting the plausible dynamic and responsive nature of investor decisions.[6]

Furthermore, we observed notable variations in investment behavior among agents with varying levels of loss aversion, indicating the importance of considering investor heterogeneity in models. This consideration becomes even

[6]The existing literature demonstrates that many investors do adjust their hurdle rates (Brigham 1975; Bruner et al. 1998; Gitman and Mercurio 1982; Meier and Tarhan 2007). However, these studies do not specify the methods investors use to adjust these rates. Meier and Tarhan (2007) highlight that "the past performance of the industry that the survey firms belong to are important determinants of both hurdle rates and hurdle rate premiums." Our model also adjusts the hurdle rate based on past financial performance, thus aligning with Meier and Tarhan's findings.

more crucial in markets characterized by a high degree of investor diversity. In such cases, oversimplification through the assumption of homogeneity could result in less accurate and potentially misleading scenario results.

In summary, our research emphasizes the significance of integrating risk and loss aversion, adaptivity, and investor heterogeneity into energy investment models. Such advancements in modeling practices would result in more comprehensive representations of investor behaviors, contributing to the development of energy system models with a more explicit representation of underlying mechanisms.

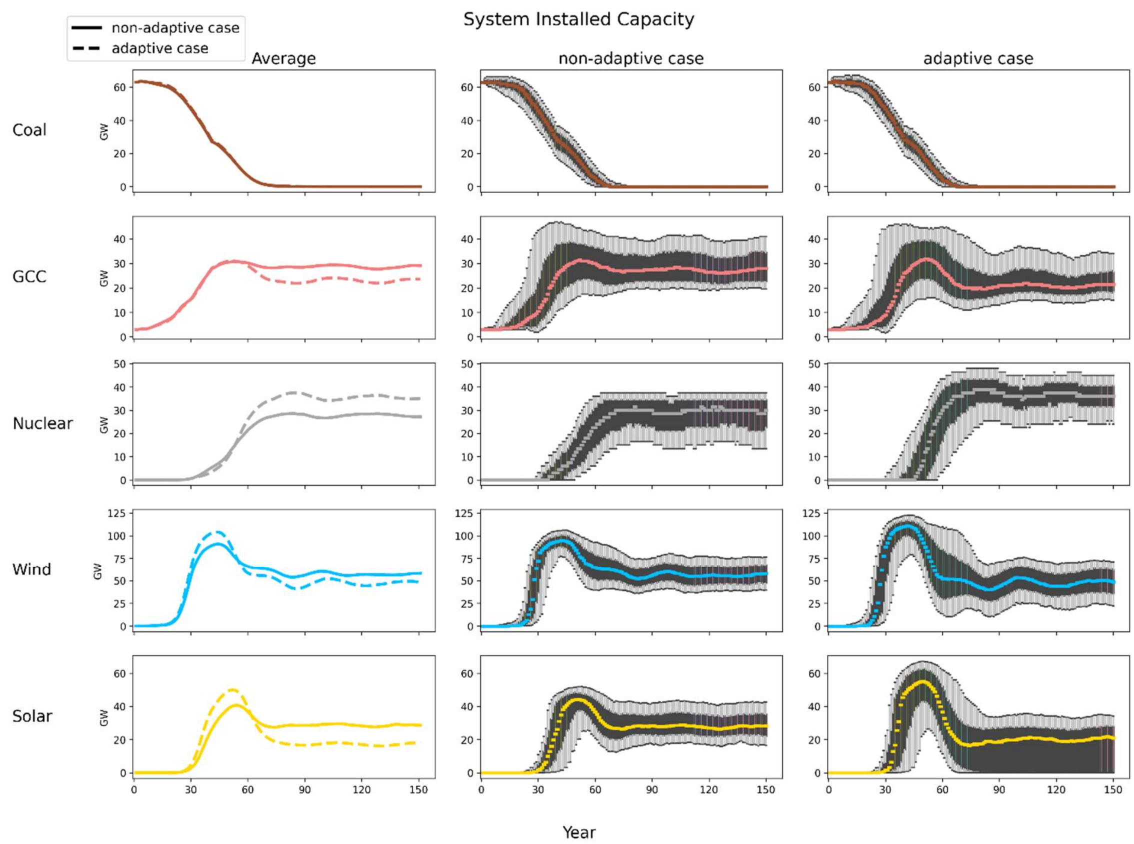


Figure 17. Evolution of installed capacity for each technology in both non-adaptive and adaptive scenarios. Each row represents a specific technology. The first column displays the average results derived from 1000 simulation runs. The second and third columns illustrate the range of installed capacity development for the non-adaptive case (second column) and adaptive case (third column). The inner shaded area in black represents the interquartile range

(25th to 75th percentiles), while the grey-colored outer range depicts the broader spread between the 10th and 90th percentiles.

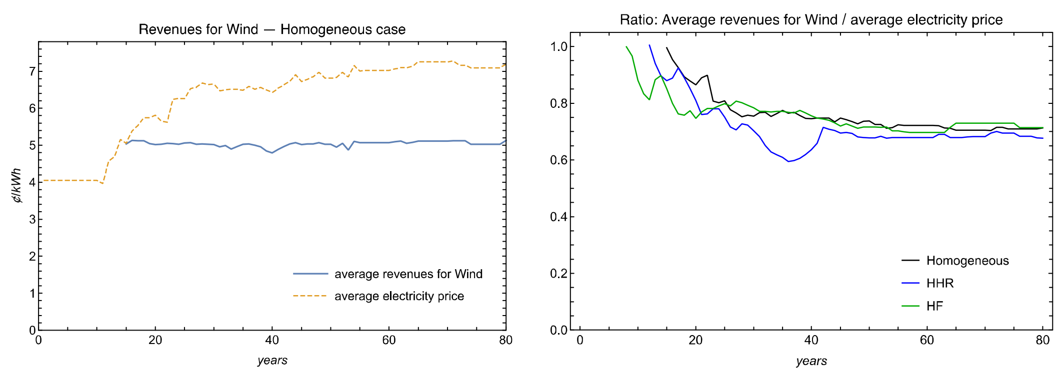
4.6 Other Findings

In addition to investigating the influences of various factors on investment decisions, our study explores the dynamics of the electricity system during the transition, including focusing on the value of wind energy.

As wind and solar technology incur no running cost, their integration into the power system tends to apply downward pressure on electricity prices when they generate electricity. This phenomenon, known as the "cannibalization effect," has been noted in previous studies (Hirth 2013; López Prol, Steininger, and Zilberman 2020). It characterizes a situation where the increased penetration of wind (and solar) power undermines its own value.

However, as shown in Fig.18, when wind energy is integrated due to an increasing carbon tax (and not as a result of investment subsidies), the average revenue per kilowatt-hour (kWh) generated by wind installations does not decrease (in absolute terms). This dynamic is driven by market forces: in a competitive market, agents will refrain from investing in wind energy if the average revenue per kWh falls below the levelized cost of wind energy. So, when the carbon tax is increased, electricity prices increase overall, and then it likely becomes profitable to invest in more wind. However, the relative value or 'wind value factor', i.e., the average revenue received by wind producers per kWh divided by the average electricity price, tends to decrease. This is because the introduction of wind energy investments exerts downward pressure on electricity prices during periods of high wind output, while the overall electricity prices continue to increase as a result of the carbon tax. Our study corroborates the findings by Brown and Reichenberg (2021), who also observed that the average revenues received by wind plants do not decline if the introduction of wind is driven by higher carbon prices.

On the other hand, if wind energy is introduced through measures such as investment subsidies, its value tends to decrease with increased installed capacity, as highlighted by Brown and Reichenberg (2021) and Hirth (2013).



(a) (b)

Figure 18. The value of wind energy when the wind is integrated due to an increasing carbon price. (a) the absolute average revenue per kWh does not drop for wind generators; (b) the relative value of —represented by the average revenue received by wind producers per kWh, divided by the average electricity price—experiences a decrease.

4.7 Reflection and Perspectives on Agent-based Models

"…all the best models are wrong. But they are fruitfully wrong." – Joshua M. Epstein (2008)

This section will further discuss the contributions and limitations of our findings, but not confine itself to dissecting the specific outcomes of the Heterogeneous Agent-based Power Plant Investment (HAPPI) model. Instead, this section will elucidate what we can infer about the real world from an abstracted agent-based model and explore how we might ascertain the validity of such ABM-derived results. At the end, this will be tied back to the broader implications of this thesis.

Insights from ABMs

Models have been employed as vital tools for investing in socio-technical systems. Despite their inexactness, models serve as useful proxies for investigating social phenomena and, hence are crucial in the analysis of complex systems. ABMs, in particular, depart fundamentally from conventional modeling types used for analyzing systems like energy systems. ABMs are sometimes constructed based on heuristic rules rather than well-defined theories. This can pose challenges in validation but also presents unique opportunities.

ABMs enable a detailed representation of heterogeneous decision-making processes and interactions at an individual level. They often account for influences on agents' decisions that fall outside conventional assumptions on rationality and cost optimization, as well as providing an explicit description of a system and its mechanisms. Among their strengths, ABMs excel in replicating adaptive behaviors and feedback loops between agents and their environment, intending to achieve a closer approximation of reality.

While some ABMs may be highly abstracted, they can nonetheless offer valuable insights into real-world phenomena. Classic ABM examples include Schelling's segregation model (Schelling 1971) and Reynolds' model of bird flocks (Reynolds 1987). These 'Picasso-style' models (Sun et al. 2016), characterized by high abstraction and simplicity, allow us to perceive reality from new perspectives.

However, questions about what can be learned from ABMs remain. Scholars hold different views regarding the explanatory power of ABMs. Epstein (2008) argues that they can clarify the underlying thought processes involved in everyday decision making by explicitly representing them, thereby enabling better understanding, testing, and replication. In contrast, Grüne-Yanoff (2009) is more skeptical, challenging the explanatory power of ABMs, stating that they do not offer comprehensive causal explanations due to their reliance on simplified, heuristic rules rather than precisely defined theories. Elsenbroich (2012), however, provides a middle-ground perspective, arguing that the limitations in providing full causal explanations are not unique to ABMs but are a common challenge in all scientific disciplines. While not perfect, ABMs can indeed offer valuable mechanistic insights into phenomena, revealing potential causal pathways (Elsenbroich 2012). Some other scholars argue that ABMs can provide a "how-possibly" explanation (Frey and Šešelja 2018; Reutlinger, Hangleiter, and Hartmann 2018). If we agree with those scholars, this implies that ABM results can, at least partially, elucidate real-world phenomena. This brings us to another question: How can we ascertain if an explanation or a result generated by an ABM is reasonable?

Validation of ABMs

Criteria for (agent-based) model validation have been a subject of debate, with prediction being a significant point of contention. Epstein (2008) downplays the role of prediction in ABM, while Thompson and Derr (2008), with reference to the "Symmetry Thesis" (Hempel and Oppenheim 1948), argue that accurate prediction is key to a model's evaluation. Troitzsch (2009) further complicates this discourse by suggesting that the type of prediction under consideration can determine its relevance for validation.

Given this ongoing debate, prediction arguably serves as a useful, albeit imperfect, measure of an ABM's explanatory power. Ideally, empirical evidence should substantiate an ABM's validity. However, due to factors such as lack of data and model idealization,[7] comparing model results with empirical data is often difficult. This brings us to the next question: In the absence of accurate prediction or empirical observation, how can we validate an ABM?

The literature (in the philosophy of science) on model validation is vast. Scholars highlight different methodologies and challenges in model validation. Weisberg (2006) and Kuorikoski, Lehtinen, and Marchionni (2010) propose two robustness analysis methodologies that hold relevance for energy system model validation.

Weisberg (2006) proposes a four-step robustness analysis: (1) identify a robust property; (2) analyze the common structure (among models) generating this property; (3) interpret the common structure as an empirical phenomenon; and (4) check the model's stability. This approach, while practical, relies on the existence of a range of similar models and assumes commonality among their structures—a premise that may not always hold. Weisberg recognizes these limitations and proposes an alternative approach, namely, to ask two alternative questions: “1. How frequently is the common structure instantiated in the relevant kind of system? 2. How equal do things have to be in order for the core structure to give rise to the robust property?” Weisberg (2006). While useful, Weisberg’s alternative approach comes with similar limitations. Such limitations are aptly described by Hacking’s (1992) insight: “The theories of the laboratory sciences are not directly compared to "the world"; they persist because they are true to phenomena produced or even created by apparatus in the laboratory and are measured by instruments that we have engineered.” In the context of Weisberg’s approach, the models serve as the 'laboratory,' and the robustness analysis functions as the 'measuring instrument' we've engineered. Consequently, robustness analysis serves as a self-vindicating method.

[7] In the philosophy of science, an idealized model is a deliberate simplification or abstraction of a complex system, aimed at making the subject more analyzable or comprehensible (Frigg and Hartmann 2006).

Kuorikoski, Lehtinen, and Marchionni (2010) propose testing specific modeling assumptions to evaluate a model's robustness. While this technique allows for thorough scrutiny of individual assumptions, it does not consider the potential cumulative impact of modifying multiple assumptions at once.

Both methods above can be useful for model validation but also present challenges and can offer only limited scopes of analysis. They remain common—and commonly accepted—ways of conducting model validation in energy system modeling, and they might be the best tools available to modelers in light of the current data and knowledge constraints.

Relating to This Study

In the context of our study with the HAPPI model, we try to capture important characteristics of the decision-making processes of investors in the electricity sector and the context within which they operate, aiming to understand their influence on the low-carbon transition.

In light of model validation discussions, we understand that complete validation of our HAPPI model is challenging, as it is with many (agent-based) models. First, from the beginning of the development of the HAPPI model, we faced challenges in finding similar models to form a common structure, thereby limiting our ability to fully employ the four-step process Weisberg proposed. Regarding Kuorikoski et al.'s methodology, we tested different assumptions in our model, scrutinizing many model factors independently (including but not limited to key factors such as the hurdle rate, capital cost, fuel cost, and learning and adaptivity) to comprehend their individual impacts on the model's outputs. Through these efforts, we've developed an enhanced understanding of our model's strengths and limitations.

5. Closing Words

The energy transition is a complex and vital area that captivates scholars across many disciplines. Within this broad landscape, this thesis delves into the critical role that investment decisions play in the development of new electricity generation capacity.

This research has focused on the development and application of agent-based models to simulate the decision-making process of investors (agents) within the context of transitioning to a low-carbon electricity system. This research analyzes how the overall electricity system responds to these investment decisions and how, in turn, the responses impact the incentives for additional investments. Our results have produced insights into the transition of the system, such as the evolution of the generation capacity mix, electricity prices, CO_2 emissions, and distribution of revenue across diverse technologies. Additionally, we have explored the economic performance of different types of investors.

This study has primarily analyzed the impact of five important factors on the agents' investment decisions: (1) the hurdle rate, (2) future carbon price expectation, (3) access to capital, (4) risk and loss aversion, and (5) learning and adaptivity. These factors represent critical dimensions influencing the decision making of investors.

The contributions from this research are two-fold. First, the findings broaden our understanding of electricity system analysis within the energy transition context. Second, this research has contributed to the development of energy system models, via the development of the HAPPI (Heterogeneous Agent-based Power Plant Investment) model. As an open-source model, HAPPI is a potential resource for future research.

Looking forward, this study opens up various trajectories for future research. Two prominent directions emerge. The first involves refining the electricity system and market representation in the model, and the second relates to enhancing our understanding and representation of the agents' (companies' and financial actors') decision-making processes.

Concerning the first direction—electricity system modeling—future investigations can delve deeper by integrating additional technologies such as battery storage and hydrogen, incorporating endogenous technology learning, and potentially extending the model's scope to other sectors like heating, industry, and transportation.

Regarding agent behavior, future research could enhance the decision-making process by refining elements like the agents' projections of future capacity mix and their ability to retire plants prematurely. The learning mechanisms employed by agents, be it learning from past experiences or learning from other agents, could be enriched by incorporating more advanced learning algorithms. Further, the heterogeneity of agents could be extended to account for diverse technology preferences, company sizes, and market power, among other aspects.

In conclusion, this thesis adds to the growing body of knowledge about energy system modeling, focusing in particular on investor decision making within the energy transition context. It provides insights on various dimensions and outlines potential directions for future research.

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Appendix