Adapting to uncertainty: Modeling adaptive investment decisions in the electricity system

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Adapting to uncertainty: Modeling adaptive investment decisions in the electricity system

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HIGHLIGHTS

- Low carbon electricity system transition driven by investor decisions.
- New method factors in price uncertainties, dynamic hurdle rates, and loss aversion.
- Low loss aversion investors exhibit a higher propensity to invest, but face heightened bankruptcy risks.

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ABSTRACT

The electricity system is undergoing a rapid transformation, with the decisions of investors significantly shaping not only the future supply mix of the system, but also dictating the pace of this transition. Given the sector's inherent complexities and uncertainties, investors are actively adapting their strategies to respond to evolving investment conditions. Effective policy design for low-carbon transition hinges on an understanding of these investment decisions. Traditional energy system models, however, often default to a simplistic view of static investment behavior, falling short of capturing the dynamics of adaptive decision-making. In response to these challenges, our study underscores the necessity of integrating adaptive investment decisions into energy system modeling. We introduce a novel approach to model investment decisions that accommodate the dynamic nature of hurdle rates, the uncertainties tied to the economic performance of various power plant technologies, and differences in investors' levels of loss aversion. While conceptual, the model's scale is comparable to the electricity market of a country such as Germany. Our findings underscore the differences in investment decisions among adaptive and non-adaptive investors. In adaptive scenario, agents initially invest more in wind and solar technologies, but less in later years compared to the no-adaptive case. Furthermore, adaptive agents with less aversion to losses show higher equity values, but also face increased bankruptcy risks. By enhancing our modeling approach to incorporate heterogeneity in adaptive investment decisions, this study aims to contribute to the ongoing discourse on low-carbon energy transition and further development of energy system models.

1. Introduction

Investments in low-carbon power generation technologies are crucial for the global transition towards a zero-emission energy system [17,20]. Investors play a vital role in this process, as their financial support provides the capital needed for investments in these technologies.

While investments in low-carbon technologies like wind and solar have been increasing rapidly during the past decades, the need for further investments remains substantial [19]. However, investors confront significant uncertainties and risks when deciding which technologies to support, given the unpredictable nature of factors such as energy demand, technology performance, market conditions and policy landscapes.

To manage risk and improve potential returns, investors adapt their investment decisions in response to changes in the market and political conditions [7,9,10,29,32]. Within the energy system context, these adaptive decisions influence the generation technologies investors choose and ultimately determine the pace of transition to a low-carbon energy system. An example of this is the adaptive strategies of investors in Germany in response to Germany's Energiewende ("energy transition") policy. This policy integrated feed-in tariffs and other incentives for renewable energy generation, prompting investors to adapt their

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strategies and reallocate capital towards wind and solar power projects, thereby aiding Germany in accelerating its transition towards a low-carbon energy system [4].

In this study, we aim to gain a deeper understanding of how investors' adaptive behavior influences their investment decisions within the electricity system and how this behavior contributes to the low-carbon transition. To achieve this, computational modeling emerges as a powerful tool and is commonly used for studying future energy systems and simulating the complex interactions between investors, technologies, and market dynamics, as evident by several literature review studies including [3,33,36].

In this study, we focus on the electricity system, assessing how individual investment decisions influence its transition towards low-carbon solutions over the long term. To simulate these individual investments, we employ a simulation technique known as agent-based modeling. This approach is particularly suited for this study, as it involves the use of 'agents'—individual entities that make decisions and interact with their environment. These agents are characterized by their autonomy and adaptability, each following own decision-making processes and rules, as noted by Bonabeau [5].

Over recent years, several agent-based modeling tools have been developed specifically for analyzing investment decisions in the electricity sector, especially in the context of its low-carbon transition. Notable examples include the works of Chappin [11], Mittal and Krejci [31], Chen et al. [12], Kraan et al. [28], Fraunholz et al. [15], Barazza and Strachan [2], Kell [24], Mason et al. [30], and Tao et al. [35].

However, a notable gap exists in existing models: they often overlook investors' adaptive behavior. To our knowledge, only a handful of modeling studies have explicitly considered investors' adaptive behavior in the context of investments in power generation technologies. Noteworthy among these are: Kraan et al. [28], Chen et al. [12] and Barazza and Strachan [2]. Neglecting to account for this behavior can lead to oversimplified representations of the decision-making process and potentially misleading assessments of future investment trends.

In the three aforementioned studies by Kraan et al. [28], Chen et al. [12] and Barazza and Strachan [2], investors adapt their investment decisions based on the profitability of their existing plants, but the exact adaptation rule is modeled differently in each study. Kraan et al. [28] capture investors' adaptivity by employing dynamic discount rates for the investor's entire portfolio. The profitability of investors' portfolios dictates whether their discount rates will increase due to low profitability or decrease when profitability is high. If an investor's discount rate exceeds a threshold, the investor goes bankrupt. In Chen et al. [12], investors exhibit varying preferences for distinct technologies. Their preferences are adjusted according to the historical profitability of each technology, employing a preference parameter that ranges from 0.95 to 1.05. This parameter is then multiplied to adjust the utility value linked to investing in a specific technology, which ultimately dictates the investor's final investment decision. In Barazza and Strachan [2], the investors evaluate a plant's cumulative profits over the previous five years. If the profit index for the investment in this technology over the past five years is negative, the investment is then deemed unprofitable. If the plant continues to be unprofitable beyond the loss tolerance threshold of an investor, then investors will not invest in the same technology until it becomes profitable again.

In this study, we build on existing literature and endeavor to enhance the modeling representation of adaptive investment decisions in new power plants. We focus on the investment decisions of power companies.

Similar to the studies by Kraan et al. [28], Chen et al. [12] and Barazza and Strachan [2], our study also employs the agent-based modeling (ABM) approach. The ABM approach is well-suited for this study due to its ability to capture the emergent behavior of the system (e.g., energy transition) by modeling the behavior (e.g., investors' investment decisions) and interactions between agents and their environment (e.g., investors and the electricity market). More importantly, agent-based models can represent the learning and adaptation processes of agents (e.g., investors' adaptive investment strategies), enabling this study to thoroughly analyze how adaptive behavior affects investors' decisions and the overall dynamics of the transition. Moreover, agent-based models are particularly adept at capturing the heterogeneity and complexity of decision-making processes among individual agents (e.g., different types of investors).

Similar to the studies by Kraan et al. [28], Chen et al. [12] and Barazza and Strachan [2], our study also enables agents to adapt their investment decisions according to the profitability of their existing plants, but in contrast to these three studies, our study takes into account that investors have varying hurdle rates for different power generation technologies [13,14,18,32]. A hurdle rate is the minimum rate of return on an investment required by an investor [25]. Investors use hurdle rates in discounted cash flow analysis to determine the net present value (NPV) or to compare with an investment's internal rate of return (IRR). In both cases, the hurdle rate is critical for assessing an investment's economic value and deciding whether to pursue a project.

Furthermore, our study acknowledges that investors or companies respond differently to changes in market conditions [27,34,38]. Specifically, the variety in investors' levels of loss aversion. We adjust investors' hurdle rates based on their individual degrees of loss aversion. The concept of loss aversion, posits that individuals often give more weight to potential losses than to equal gains [22]. Although Kahneman and Tversky's research predominantly targets individual decision-making, empirical evidence suggests that organization-level entities may also exhibit characteristics of loss aversion [23,39]. In this study, we refer to the concept of loss aversion as varying degrees of tolerance towards potential losses.

Additionally, unlike the three previously mentioned studies by Kraan et al. [28], Chen et al. [12] and Barazza and Strachan [2], this study also takes into account that investment is subject to various sources of uncertainty in the power sector, explicitly integrating economic and regulatory uncertainties in the model. Economic uncertainties are captured by the variability of future electricity demand and fuel prices, which include coal, natural gas, biogas, and nuclear fuels, while regulatory uncertainty is represented through the variability of carbon prices.

Moreover, although the previous three studies have incorporated adaptive behavior in investors' decision-making processes, Kraan et al. [28], Chen et al. [12] did not specifically analyze the impact of adaptive behavior on their investment choices. In other words, they include adaptive behavior as a component of their models, but do not specifically analyze the consequent impacts on investment decisions. Our study aims to thoroughly explore and analyze the effects of investors' adaptive behavior on their investment choices. While Barazza and Strachan [2] did not examine the effect on the development of the low-carbon transition. In contrast, our study focuses on investigating both aspects of investors' adaptive behavior and its impact on the energy transition. In addition, this study also explored the dynamic interplay among investment decisions, technology performances and market conditions.

Lastly, contrasting with the many models mentioned above, which are not open source, our model adopts a more transparent approach. It is fully open source, with its code readily accessible via a weblink provided in Section 2.1. This openness not only ensures transparency regarding our model's structure and implementation but also positions it as a potential useful tool for future research endeavors.

To summarize, this research aims to contribute to the existing literature by enhancing the modeling representation of companies' adaptive investment decisions in the power sector. We present a novel agent-based approach to model investor behavior. This approach considers the adaptation of hurdle rates based on past economic performances specific to technologies, as well as the varying loss aversion levels among companies. Furthermore, this research aims to offer insights into the impact of companies' adaptive behavior on their investment choices, in comparison to non-adaptive ones. This study also takes into account uncertainties in market conditions. By shedding light on the impact of investors' companies' decisions under these conditions on the evolution of the electricity system's capacity mix and pricing, this research seeks to offer knowledge for both energy system modelers and policymakers working towards a low-carbon transition in the power sector.

The remainder of this paper is structured as follows: Section 2 outlines the basic model structure, and in particular, describes the adaptation rule, and presents the experimental design. Section 3 presents and discusses the results. In Section 4, we present a summary of the sensitivity analysis. Finally, Section 5 concludes the paper with a summary of our findings and their implications.

2. Method

2.1. Model description

From a broader perspective, this study employs agent-based modeling techniques to simulate individual agents' investment decisions and analyze the impact of these decisions on the overall system's capacity mix and electricity price. Additionally, it examines the low-carbon transition of the electricity system and individual agents' financial performance.

Building on previous studies [21,42–44], we develop the model by including adaptive hurdle rates in agents' decision-making processes, as well as by incorporating stochastic prices and stochastic electricity demand.

This section will briefly describe the model with a focus on the adaptive rules. For a more detailed model description, one can look at the document at https://github.com/happiABM. The model code, implemented in Python 3.9, is open source and available at the same web location.

2.2. Basic model framework

This research employs a conceptual model of the electricity system. In our model, the agents are power companies that invest in, own, and run power plants. The model simulates agents' investment decisions along with the supply and demand dynamics in the electricity market. There are five types of technologies that agents can choose to invest in — coal-fired plants, gas combined cycles plants (GCC)[1], nuclear plants, wind, and solar photovoltaics (PV). Parameters for the power plants such as capital costs, size, emission intensity, etc. are provided in the supplementary. The simulation starts at a zero-carbon price and with only coal-fired and GCC power plants, which is the model steady-state solution without any stochasticity in prices and demand. These initial plants have varying lifetimes left and belong to an additional agent who does not engage in any new investments. In contrast, there are active agents starting with zero capacity but equipped with an initial capital of one billion euros. This capital enables these active agents to afford investments in a few power plants from the first year.[2] Subsequently, each year, power plants reaching the end of their lifetime are removed from the system, and agents take turns evaluating and making new investments. This process, in turn, influences investments in later years by affecting the supply mix, electricity prices, and profitability of various technology types. As the outdated power plants are phased out and new investments are introduced, the system capacity undergoes a continuous evolution over time.

[1] The GCC plant is fueled by either natural gas or biogas, depending on which has the lower operating cost when the carbon price is considered, i.e., natural gas and biogas are perfect substitutes.

[2] In our model, each agent must finance 30% of a power plant's capital cost using their own funds. Given the capital costs of different types of power plants (listed in Table S3 of the supplementary materials), this initial capital enables agents to finance either three coal power plants or approximately eight gas combined cycle (GCC) plants. Notably, as the carbon price is set at zero during the initial 10 years, investing in other technologies apart from coal and GCC is not economically viable within this period.

2.3. Profitability evaluation

Each year, agents take (randomly assigned) turns to make investment evaluations. Every agent assesses each type of technology individually, and then makes a final investment decision based on the expected profitability of each option. They choose the technology expected to provide the highest positive return.

The agent employs the following steps to assess the potential profitability of an investment: first, the agent adds a hypothetical power plant of the type being examined to the existing capacity mix. Next, the agent forecasts future electricity demand, carbon prices, and fuel prices. This is done by using moving averages based on data from the previous five years. The agent then assumes these values will stay constant throughout the entire lifespan of the plant being assessed.

Subsequently, the agent uses the forecasted values of the future electricity demand, carbon prices, and fuel prices to estimate the annual revenue streams throughout the lifetime of the potential plant. This is done by running the dispatch module of the model, which calculates the electricity price and production from the plant being assessed for the forthcoming year. The agents assume that the conditions remain for the whole plant's lifetime.

The agent then discounts and aggregates all future revenue streams to calculate the net present value (NPV) of investing in the potential plant. The NPV is then divided by the plant's capital cost, denoted as I. This adjustment is beneficial when comparing plants of different scales or sizes as it provides a relative measure. Also, when funds are limited, one should pick the projects that offer the highest NPV per dollar of initial outlay [6]. This process determines the profitability index of investing in this potential plant of type T, denoted as π_T.

$$\pi_T = \frac{NPV}{I} \tag{1}$$

$$NPV = \sum_{t=1}^{L} \frac{r_t - c_t}{\left(1+\gamma_t^T\right)^t} - I \tag{2}$$

- r_t is the annual revenue generated by selling electricity from the hypothetical 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 is the plant's lifetime.

When evaluating the NPV of a potential investment, agents need to select a hurdle rate γ to discount future revenue streams as depicted in Eq. (2). As mentioned in the previous section, the hurdle rate is the minimum rate of return required for an investment to be considered worthwhile. The selection of hurdle rate significantly influences the anticipated profits of an investment option.

Rather than utilizing a fixed hurdle rate as commonly found in energy system modeling studies, this study allows agents to adapt their hurdle rates in response to shifting market conditions, or more specifically to how well previous investments in various technologies have performed.

2.4. The adaptive rule

The agent employs a distinct hurdle rate for each technology and adjusts it annually based on the historical economic performance of the respective technology, along with assumptions on the agent's loss aversion level. The agent uses two indicators to adapt the hurdle rate for a given technology.

The first indicator is the average ex-post profitability of a specific technology T over the past N years at year t, denoted as $\overline{C}_t^T$.

$$\overline{C}_t^T = \sum_{n=t-N}^{n=t-1} \frac{C_n^T}{N} \tag{3}$$

where $N = 5$, representing a 5-year duration. C_n^T is the ex-post profitability indicator in a given year n for the specific type of technology T and $C_n^T = r_n^T - c_n^T - a_n^T$, i.e., the annual revenue r_n^T minus the operating cost c_n^T and minus the annuitized capital cost of the plant a_n^T. The annuitized cost of a plant is calculated as:

$$a_n^T = I \cdot \frac{\mu}{1-(1+\mu)^{-L}} \tag{4}$$

- I is the capital cost of the plant.
- μ is the annual bank interest rate.
- L is the plant's lifetime.

The second indicator used to adjust the hurdle rate is the occurrence of positive annual profitability over the past N years, i.e.,

$$m_t^T = \sum_{n=t-N}^{n=t-1} if\ \left[C_n^T > 0\right]\ then\ 1, else\ 0. \tag{5}$$

where m_t^T represents the number of years for which the ex-post profitability is positive over the past N years. Then m_t^T is used to compare with a threshold value λ. The λ represents an agent's loss averse level. The higher the loss averse level, the larger λ. This approach resembles a retrospective application of the Value at Risk (VaR) method as it involves assessing the probability of losses and comparing them against a predefined threshold [25]. In this case, the loss distribution used by the agents is determined based on the experiences from the previous N years.

For each technology, if $\overline{C}_t^T \geq 0$ and if $m_t^T \geq \lambda$, then the agent will decrease the hurdle rate by 0.5 percentage points. On the other hand, if $\overline{C}_t^T < 0$ and $m_t^T \leq \lambda$, the agent will increase the hurdle rate by 0.5 percentage points. In other conditions, the agent will keep the hurdle rate the same as last year. The minimum hurdle rate is 4% per year, matching the 4% yearly bank interest rate assumed in this study, i.e., $\mu = 4\%/year$[3].

2.5. The financial module

This model also incorporates a financial module that monitors individual agents' financial metrics, including cash, net annual income, debt level, and equity.

This study assumes that each agent begins with an initial cash balance of one billion euros. When investing, the agent is required to contribute 30% of the capital cost for each investment from their own account, while the remaining 70% is procured as a loan from the bank[4], subject to a 4% annual interest rate. The loan is amortized and must be repaid over the course of the plant's expected operational lifespan.

Before proceeding with an investment, the agent must first ensure that it has sufficient cash to cover its interest charges and annuitized principal payments for the upcoming year. These obligations must be settled at the beginning of each year. If the agent has enough remaining cash after covering these expenses, it can proceed with the chosen investment; otherwise, it will not be permitted to make further investments in the current year.

If an agent's equity value falls below zero, the agent is deemed bankrupt and will be prohibited from making any further investments, but will continue operating its power plants. In this case, a new agent will be introduced into the system. The new agent starts with an initial capital and has the same initial risk aversion level as the bankrupted agent.

For a comprehensive overview of the financial module and the whole model, readers are encouraged to consult the online model documentation at https://github.com/happiABM.

2.6. Experiment setup

The simulation starts at year 0 and runs for 150 years. The electricity system commences with coal and gas power plants, with installed capacities of 64 GW and 2 GW, respectively, whose capacities reflect the steady-state solution for the model when the carbon price is zero and no stochasticity in fuel prices or electricity demand. Each year, plants that have reached the end of their operational lifespan are removed from the system, and agents assess new investment opportunities.

Based on Jonson et al. [21], we employ 64 time slices to characterize the yearly variability of wind and solar energy, as well as fluctuations in electricity demand. While the model is not a direct representation of any specific existing system, the variability parameter reflects a country's weather conditions and electricity demand, similar to Germany (see Table S1 in the Supplementary material for specific parameter values). The electricity demand, in response to its price, is assumed to follow an isoelastic function [21] and we assume that there is no exogenous trend influencing electricity demand.

Carbon prices, fuel prices, and electricity demand (driven by other factors than prices) are assumed to adhere to stochastic processes as illustrated in Fig.1. The parameter values are established through a first-order autoregressive model (AR1), as demonstrated in Eq. (6).

$$p_{t+1} = p_t + \varepsilon_1 \cdot (\overline{p} - p_t) + \varepsilon_2 \cdot \overline{p} \cdot \sigma \tag{6}$$

where

p_{t+1} is the price at time $t+1$.

p_t is the price at time t.

ε_1 is a constant that determines the weight of the mean reversion component.

$\overline{p}$: is the long-term mean price.

ε_2 : is a constant that determines the weight of the stochastic component.

σ : is the volatility, which measures the level of fluctuations in the price.

We simulate a scenario with a progressively increasing carbon price. The carbon price is initially set to zero for the first 10 years, but after that period, it follows a stochastic process with an upward trend, reaching an average of 100 euros per ton/CO_2 around year 60. Additionally, the fuel prices–including coal, natural gas, biogas, and nuclear fuel, as well as electricity demand, also follow a stochastic process. However, the expected long-term mean of these variables remains constant, as illustrated in Fig. 1. The parameter values used to determine the fuel prices, carbon prices and electricity demand are listed in the supplementary material.

2.7. Case design for the main analysis

With this model setup, we investigate our research question by constructing two main cases – (1) a non-adaptive case, and (2) an

[3] This study simulates an electricity system comparable in size to that of Germany. Based on historical interest rate data from Germany between 2003 and 2023, the peak rate during this period reached 6.55%, while the lowest point was at 1.76% Trading Economics [37]. Germany Bank Lending Rate. https://tradingeconomics.com/germany/bank-lending-rate.. Overall, the average interest rate throughout these two decades approximates to 4%.

[4] IEA [16]. The cost of capital in clean energy transitions. https://www.iea.org/articles/the-cost-of-capital-in-clean-energy-transitions, International Energy Agency, Paris. estimates that the typical capital structure of low-carbon generation investments in advanced economies is 33% equity and 67% debt, while 36% equity and 64% debt for developing economies.

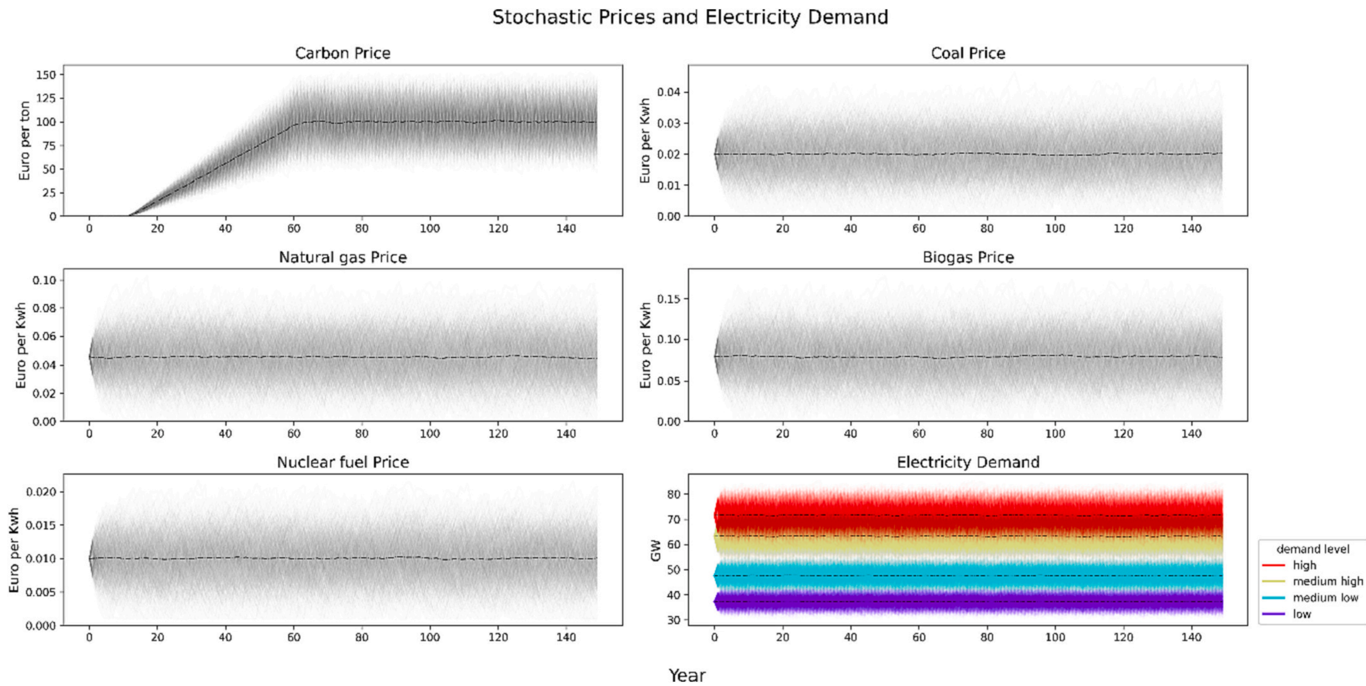


Fig. 1. An illustration of the implementation of stochastic fuel prices and electricity demand. Each solid line represents the value realized in a single run and the dashed black line represents the mean value. The values follow mean reverting stochastic processes. For more details on the generation and implementation, please refer to the supplementary material Section S1.

adaptive case. In both cases, we have four representative agents. In the non-adaptive case, all agents keep a fixed hurdle rate – 6%/year for all technologies throughout the simulation. In the adaptive case, all agents begin with a hurdle rate of 6% per year. However, they have the ability to adapt according to each technology's performance as described in the previous section, and they exhibit varying levels of loss aversion. Among them, one agent is loss neutral with $\lambda = 0$, meaning that when making investment decisions, this agent only takes into account the average economic performance of a technology as defined in Eq. (3). The other three agents are loss averse, with $\lambda = 1$, $\lambda = 3$, and $\lambda = 5$, respectively. This indicates that, in addition to considering the average economic performance, these agents also account for the number of times a particular technology has generated negative profitability over the past five years and use this information to create a loss distribution.

Each case is executed 1000 times with distinct realizations of the stochastic process. We then compare and analyze the outcomes at two levels — the electricity system level and the individual agent level. On the system level, we present the evolution of the capacity mix, the average electricity price and its volatility, and the economic performances of different technologies over time. At the agent's level, we present each agent's investment decisions, hurdle rates and financial performances.

In addition, in the sensitivity analysis, we investigate more cases with varying assumptions regarding three key factors in our model: (1) stochastic processes, (2) capital costs of nuclear power plants, and (3) methods for forecasting future carbon and fuel prices.

3. Results and discussion

3.1. Installed capacity

Fig. 2 displays the evolution of the capacity mix and the CO_2 emission in the system in both the *non-adaptive* case and the *adaptive* case. The figure shows the average value derived over the 1000 runs. In both cases, the system begins with coal and gas power plants, and gradually transits towards low-carbon energy sources as the carbon price rises over time. As coal is phased out and biogas is used as an alternative to natural gas in the GCC plant, emissions gradually decrease over time, eventually reaching zero after approximately year 60 on average.

Wind power is the first low-carbon technology that expands, followed by solar photovoltaics (PV) and nuclear power. After the initial expansion, the capacity of wind declines around year 50 when nuclear starts to expand. For a comprehensive examination of the interplay between various technologies, please see [21,43]. The system capacity reaches a stable mix approximately 90 years into the simulation. By this juncture, all coal-fired power plants have been phased out, due to the high carbon price.

Fig. 3 illustrates the difference in installed system capacity when comparing the non-adaptive case with the adaptive case. These differences can be observed during both the capacity expansion phase of wind and solar (approximately year 10 to 60) and the post-expansion phase of these technologies, albeit with distinct directional tendencies during these two phases.

Throughout the expansion phase especially around year 30 to 60, it is evident that the adaptive case features, on average, a higher prevalence of wind and solar capacities, along with a modest rise in GCC and a marginal reduction in nuclear capacity compared to the non-adaptive case (see the first columns in Fig.3). Conversely, in the post-expansion phase after around year 60, the adaptive case displays a lower capacity of wind, solar, and GCC, while nuclear capacity is significantly higher relative to the non-adaptive case.

Moreover, these two cases also display differences in the distributions of the installed capacities across various technologies. These variations are based on different realizations of the stochastic process for fuel prices, carbon prices, and electricity demand (see the second and third columns in Fig.3). The difference between the non-adaptive and the adaptive cases is especially clear after year 50. We can see that in the non-adaptive case, there is a wider range between the 10th and 90th percentile for GCC and nuclear capacity while the adaptive case has a wider range in wind and solar capacities. This indicates that the attractiveness to invest in solar and wind is more sensitive to the realization of the different stochastic processes than what GCC and nuclear

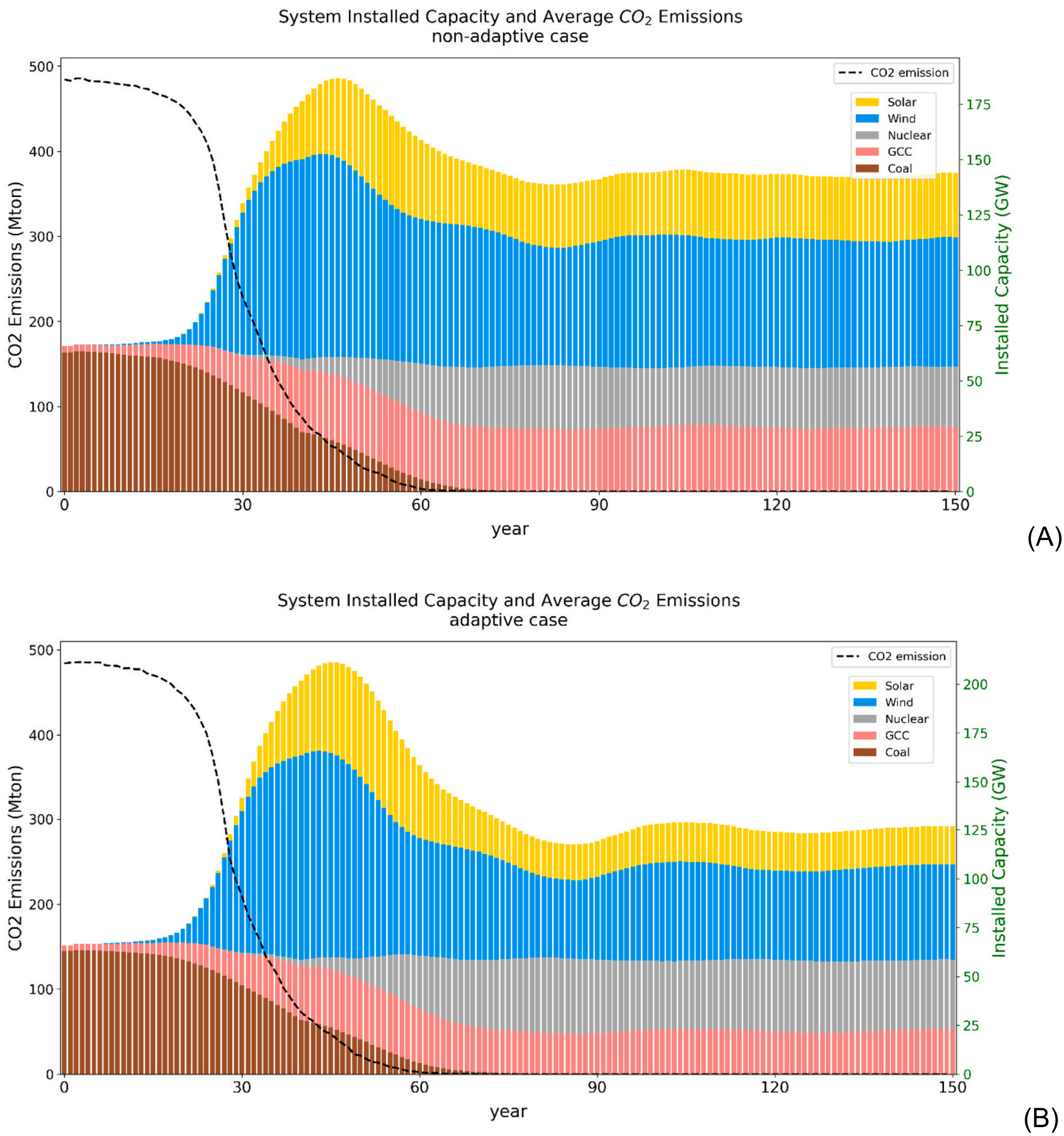


Fig. 2. The development of the system installed capacity and the corresponding CO_2 emissions (black dashed line) over a period of 150 years. Panel (A) illustrates the non-adaptive case. Panel (B) illustrates the adaptive case. The results in each panel are the average values from 1000 simulation runs.

are.

3.2. Individual agents' investments

The annual investments of individual agents in the non-adaptive case (Fig. 4a) and the adaptive case (Fig. 4b) show that agents initially, when the carbon price is zero, invest primarily in coal and some GCC power plants. As carbon prices rise, investments in coal decline, and those in GCC and wind power expand. As the profitability of using coal power declines even further, investments in coal drop to zero. Around year 30, investments in wind peak. Owing to the rapid increase in wind power plants and their approximately 25-year lifespan, we observe recurring peaks in wind power investments every 25 years across the remaining model time horizon. These peaks represent new investments made to replace retiring plants.

Following the investment peak in wind around year 30, agents begin to invest in nuclear power as it becomes competitive, as a result of increasing carbon prices. This implies that the complementary system of wind and GCC becomes more costly to use, see Jonson et al. [21] and Yang et al. [43] for a discussion.

Fig. 4 also demonstrates the differences between the two cases. In the non-adaptive scenario, the agents' uniform investment strategies lead to

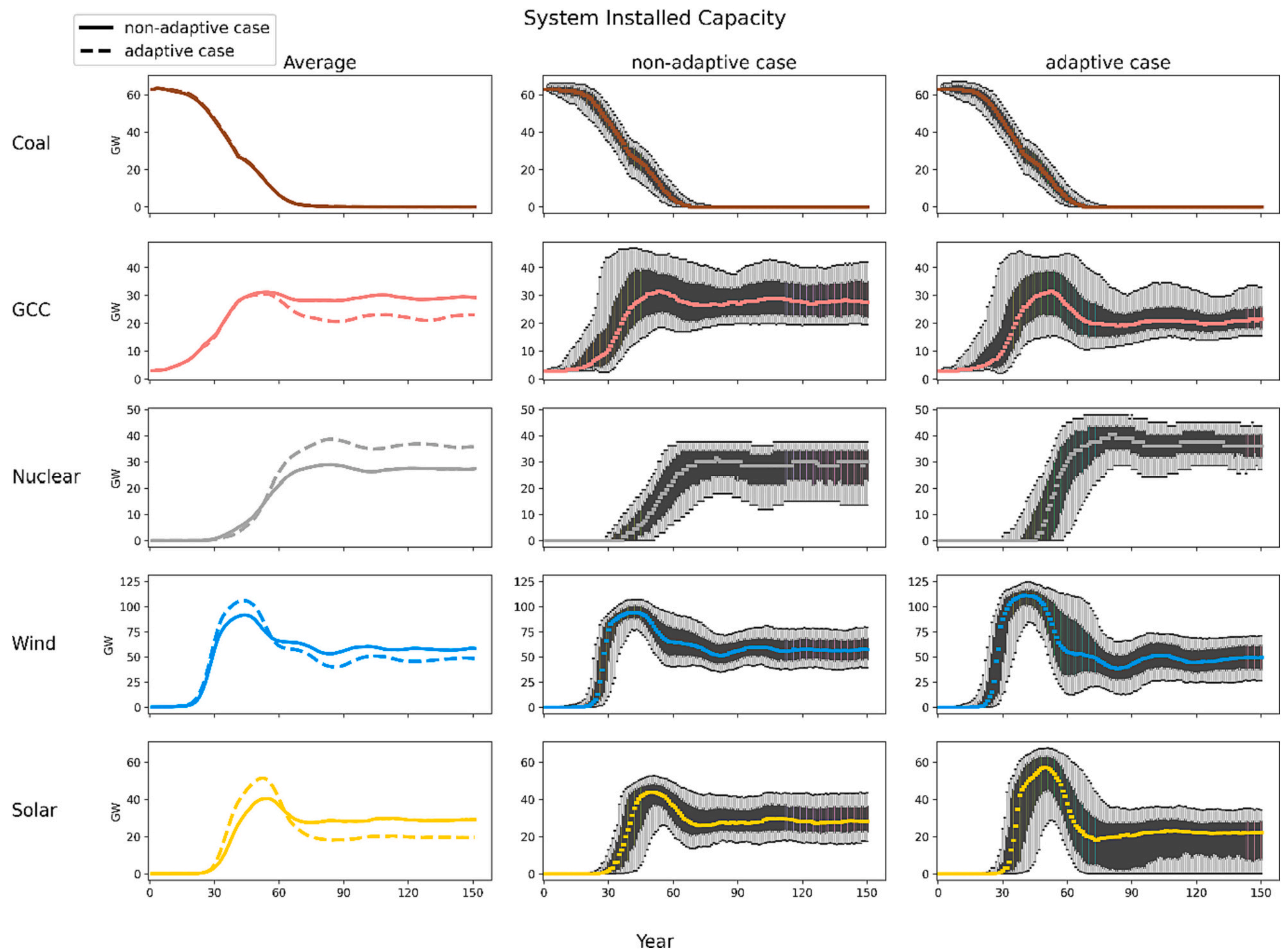


Fig. 3. Evolution of system installed capacity for each technology in both non-adaptive and adaptive scenarios. Each row represents a specific technology. The first column displays the average results derived from 1000 simulation runs. The second and third columns illustrate the range of installed capacity 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.

homogeneous investment decisions. Conversely, in the adaptive case, adaptive hurdle rates and heterogeneous loss aversion levels lead to diverse investment decisions, with less loss-averse agents investing more. In addition, during the expansion phase of wind and solar, adaptive agents together invest more in wind and solar compared to non-adaptive agents. During this period, even the agent with the highest loss aversion ($\lambda = 5$) invests a significant amount, only marginally lower than the agents in the non-adaptive scenario. Conversely, in the post-expansion phase, the trend shifts as adaptive agents collectively invest less in wind, solar, and GCC technologies, while increasing their investments in nuclear power. Even though the least loss-averse agent ($\lambda = 0$) invests more in every technology compared to an agent in the non-adaptive case, the other three adaptive agents with higher loss-averse levels reduced their investments especially in wind and solar compared to the non-adaptive agents. This accounts for the differing installed capacity levels observed between the two cases at the system level as shown in Fig. 3.

Further, one can also note that in relative terms, looking at the share of investment in the different technologies, the adaptive agents make fewer investments in wind and solar the more loss-averse they are.

To dig further, the distinct investment decisions among agents stem from the varying hurdle rates employed in these two cases. In contrast to the non-adaptive case, where agents maintain a fixed hurdle rate of 6% per year, agents in the adaptive case adjust their hurdle rates for each technology according to the technology's financial performance and the agent's risk aversion level.

Fig. 5 displays the average hurdle rates utilized by agents in the adaptive case. It is evident that initially during years 10 to 40, adaptive agents lower their wind and solar hurdle rates to below 6% per year. Additionally, the three least loss averse agents also decrease their hurdle rates for GCC. Consequently, agents in the adaptive scenario invest more in wind, solar, and GCC compared to the non-adaptive one as shown in Fig. 3 during the initial transition phase.

After approximately year 40, all agents begin to increase their hurdle rates for wind and solar, with variations depending on individual loss aversion levels. In brief, this can be explained as follows, an increase in carbon prices results in a reduced reliance on coal and gas. Concurrently, there is an increase in investments in nuclear energy. This shift puts downward pressure on solar and wind energy, subsequently leading to a decrease in their profitability and investment rates.

For GCC technology, three agents with risk aversion $\lambda = 0$, $\lambda = 1$, and $\lambda = 3$ initially decreased their hurdle rates before eventually increasing them, whereas the agent with the highest loss aversion ($\lambda = 5$) consistently raised their rates.

In the case of nuclear technology, agents with lower risk aversion ($\lambda = 0$, $\lambda = 1$) kept hurdle rates below (or near) 6% throughout the period, while those with higher risk aversion ($\lambda = 3$, $\lambda = 5$) displayed significant increases, albeit lower than the increases observed for other technologies. As demonstrated in our prior research, a lower hurdle rate tends to encourage investments in nuclear power, making it more appealing than other competitive technologies like GCC and wind energy [43].

Overall, greater loss aversion is correlated with higher increases in

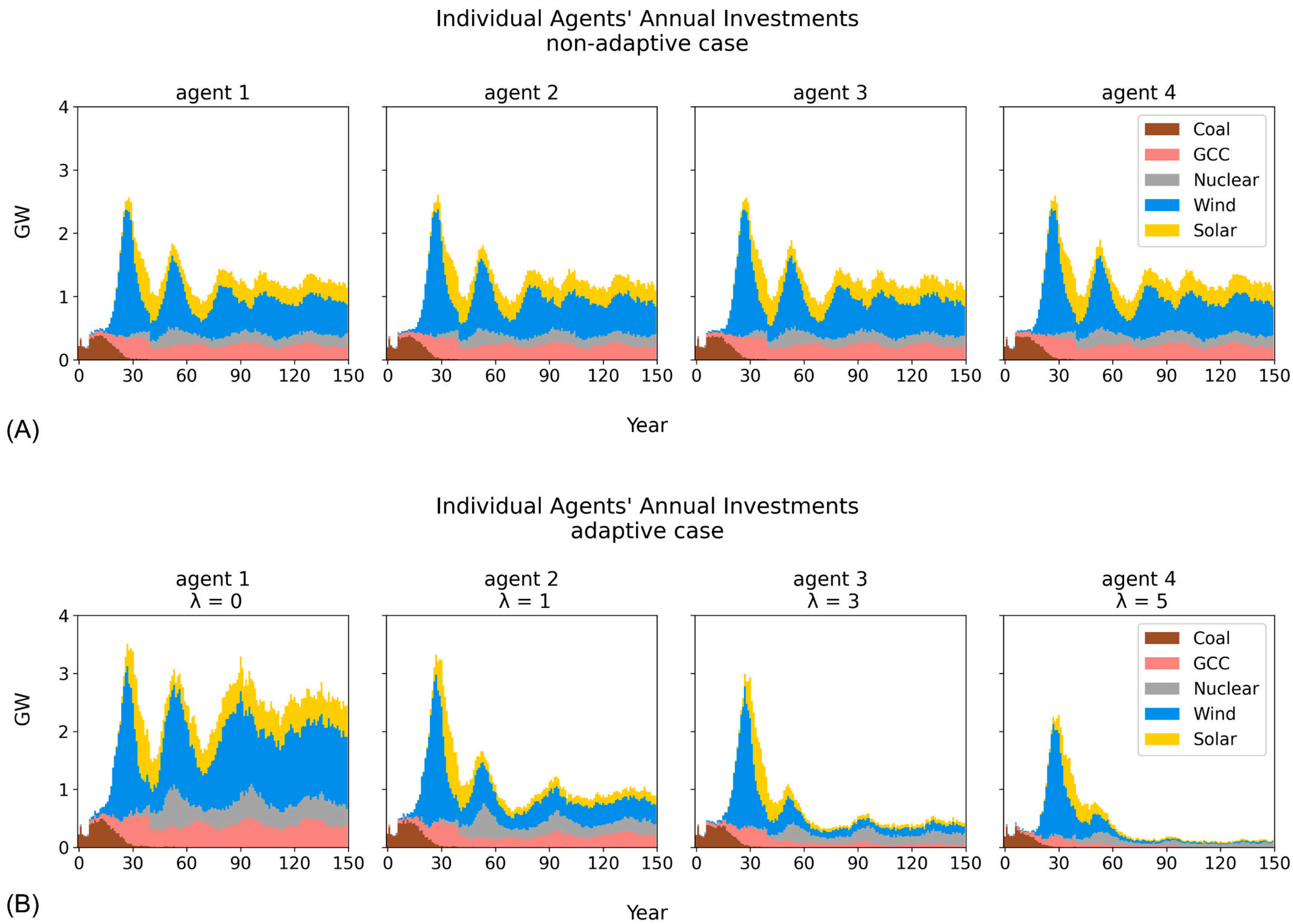


Fig. 4. Annual Investment by four individual agents: Panel A represents the non-adaptive case, while Panel B shows the adaptive case. These figures illustrate the average result derived from 1000 simulation runs. Individual runs may result in (significant) differences.

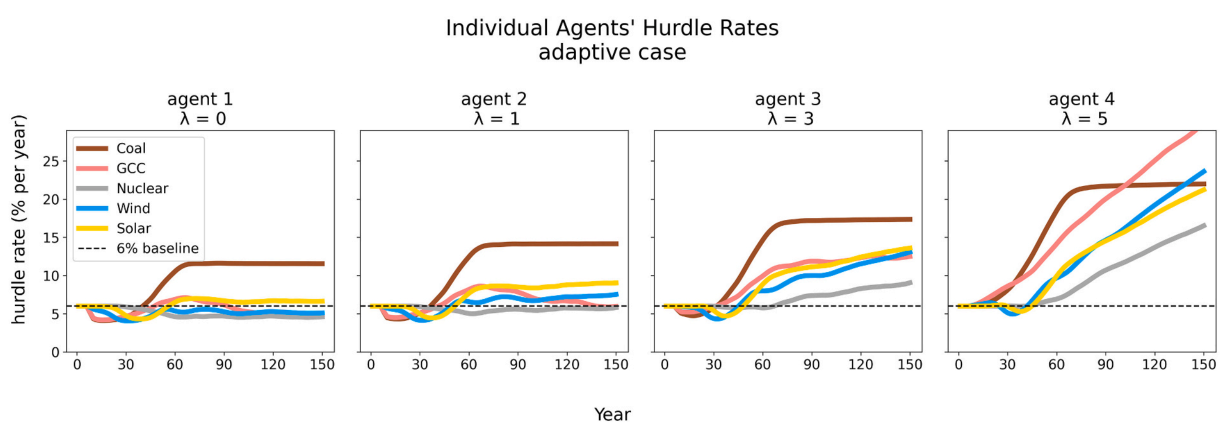


Fig. 5. Progression of four individual agents' hurdle rates in the adaptive case. (The coal hurdle rate remains constant after approximately year 60 due to the absence of coal plants in the system, resulting in a lack of modeling data for hurdle rate adjustments.) This figure illustrates the average result derived from 1000 simulation runs. Individual runs may result in (significant) differences.

hurdle rates. To understand the reasons behind agents adjusting their hurdle rates in this manner, it is crucial to examine the financial performance of each technology.

3.3. Individual technologies' financial performances

This section sheds light on the financial performance of each technology. We use the five-year average ex-post profitability indicator, denoted by $\overline{C}_t^T$ (as detailed in Eq. (4)). This indicator is then normalized by dividing it by the technology's capacity, measured in MW.

As depicted in Fig. 6, the five-year average ex-post profitability per MW demonstrates distinct patterns for each technology. Observing the median values, the profitability indicator for coal decreases

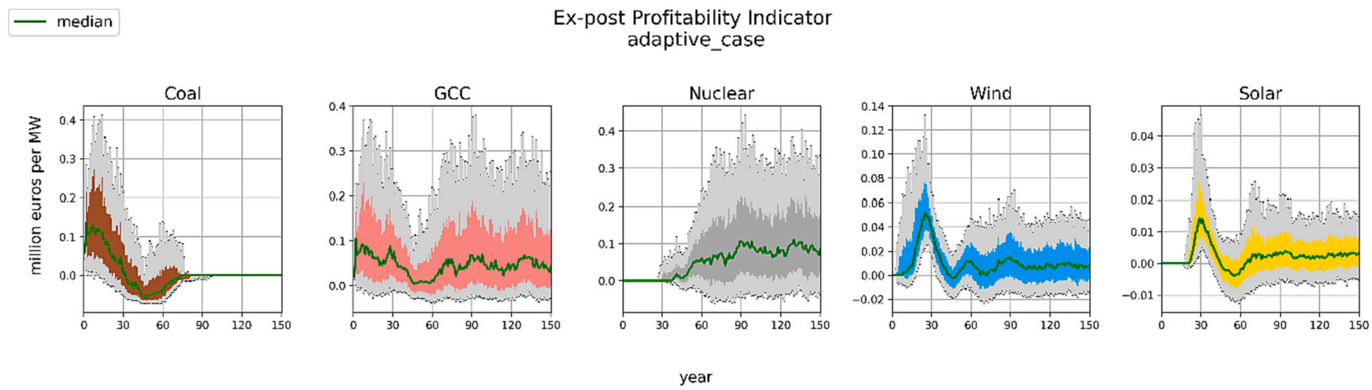


Fig. 6. Ex-post profitability indicators for each technology per MW in the adaptive case. In each panel, the inner colorfully shaded area shows the range from the first quartile (25th percentile, Q1) to the third quartile (75th percentile, Q3), and the outer lightgrey-shaded area shows the 10th percentile to the 90th percentile. The figure depicts the mean outcome of 1000 simulation runs.

continuously after the introduction of the carbon price, as the running cost for coal power plants continues to rise more than the revenues. In the GCC case, initial carbon pricing stimulates profitability growth, followed by a decline as the carbon price continues to increase. After around the 50th year, a rebound occurs due to two factors: a rise in electricity prices (elaborated in the next section), and a fuel switch from natural gas to biogas[5]. For nuclear, its ex-post profitability indicator increases during its expansion period and then stays around that level thereafter. For wind and solar, both have increased profitability in the beginning when their capacities are expanding, but then drop after around year 30 and stay at a relatively stable level thereafter.

For wind, this can be explained as shown in several previous studies (see e.g. [8,21,43]), which suggests that as wind energy is increasingly adopted due to a rise in carbon pricing, the relative value of additional wind plants, as expected, tends to decline. This is reflected in the lowering of the average electricity price received by wind producers compared to the overall average electricity price, as the installed wind capacity expands. This study also presents similar findings for solar energy, with the revenue received experiencing a downward trend as its capacity expands.

Different technologies receive varying levels of ex-post profitability, primarily because their revenues per kWh of sold electricity varies (since they produce at different time slots). As illustrated in Fig.7 (A), before the introduction of a carbon price, coal power plants were the main electricity suppliers, with GCC plants contributing during peak hours. As wind and solar capacities began to expand (Fig.7B), coal production diminished, while GCC, wind, and solar production increased. Interestingly, during this period, wind and solar energy were occasionally produced at almost zero price. With subsequent increases in carbon price (Fig.7C), coal production declined further, primarily serving peak hours. Meanwhile, GCC plants switched from natural gas to biogas, and nuclear power started to contribute to the electricity supply. Eventually, when coal was phased out and the system capacity mix achieved a more stable state, nuclear energy emerged as the dominant source of electricity production, providing power during both low and high electricity price periods. GCC primarily generated power during high-price periods, while wind and solar energy production was mainly concentrated in low-price periods (Fig.7D) as windy and sunny conditions cause low prices.

[5] In the absence of stochastic fuel prices, and considering the fuel cost assumptions in this study (provided in the supplementary material), the GCC plants would utilize natural gas when the carbon price is below 78 euros per ton of CO_2. However, if the carbon price rise above 78 euros per ton of CO_2, the GCC plants would switch to using biogas. In this model, the carbon price surpasses 78 euros per ton of CO_2 around year 50.

The distributions of ex-post profitability indicators of each technology displayed here correspond with the adaptation of agents' hurdle rates, as discussed in the previous section.

3.4. Electricity prices

Fig. 8 compares the electricity prices for non-adaptive and adaptive cases, revealing several noteworthy findings. Firstly, it can be seen that in both instances, due to stochastic fuel prices, carbon prices and electricity demand, annual electricity prices can vary widely.

Firstly, the average electricity price escalates during the initial phase before slightly declining and stabilizing thereafter. This initial rise is caused by the growing carbon price, which increases the electricity prices since coal and sets the electricity price during most hours (Fig. 7B). This provides an incentive to invest in wind and GCC since the CO_2 intensity is smaller for GCC than for coal power, which mitigates the increase in electricity prices.

Secondly, an interesting observation is that the upper range shrinks between years 30 and 50. This is attributable to the large investments in wind and solar during this period as elaborated in Section 3.1 and Section 3.3, together with the fact that there is a large capacity of dispatchable technologies in the system. The wind and solar power plants will lead to large production when it is windy and sunny, generating electricity at near-zero prices (Fig. 7C), During hours when solar and wind power production is low, the combined operation of coal and gas power plants, along with nuclear power plants, helps to stabilize electricity prices. This leads to relatively low annual average electricity prices.

Thirdly, after approximately year 60, all coal power plants are decommissioned, and biogas replaces natural gas as fuel for GCC plants. Consequently, electricity prices cease to increase alongside carbon prices. Nevertheless, electricity prices remain elevated compared to the beginning of the modeling period due to the higher costs associated with technologies that have replaced coal, such as nuclear power. For a more comprehensive discussion on this topic, please refer to our previous publication, Yang et al. [43], specifically Section 4.2.1.

Fourthly, as depicted in the third panel of Fig. 8, the average electricity price in the adaptive scenario is lower than in the non-adaptive scenario. This can be explained by the larger capacity and the lower hurdle rate used by the dominant agent in the adaptive case.

To gain a comprehensive understanding of electricity prices, it is essential to consider not only the prices themselves but also the associated volatility in the market. Previous studies [1,26,41,43] have demonstrated that a higher proportion of variable renewable energy sources contributes to an increased variance in electricity prices. This correlation is also evident in the present study, as illustrated in Fig. 10. In both instances, price volatility, quantified as the standard deviation of

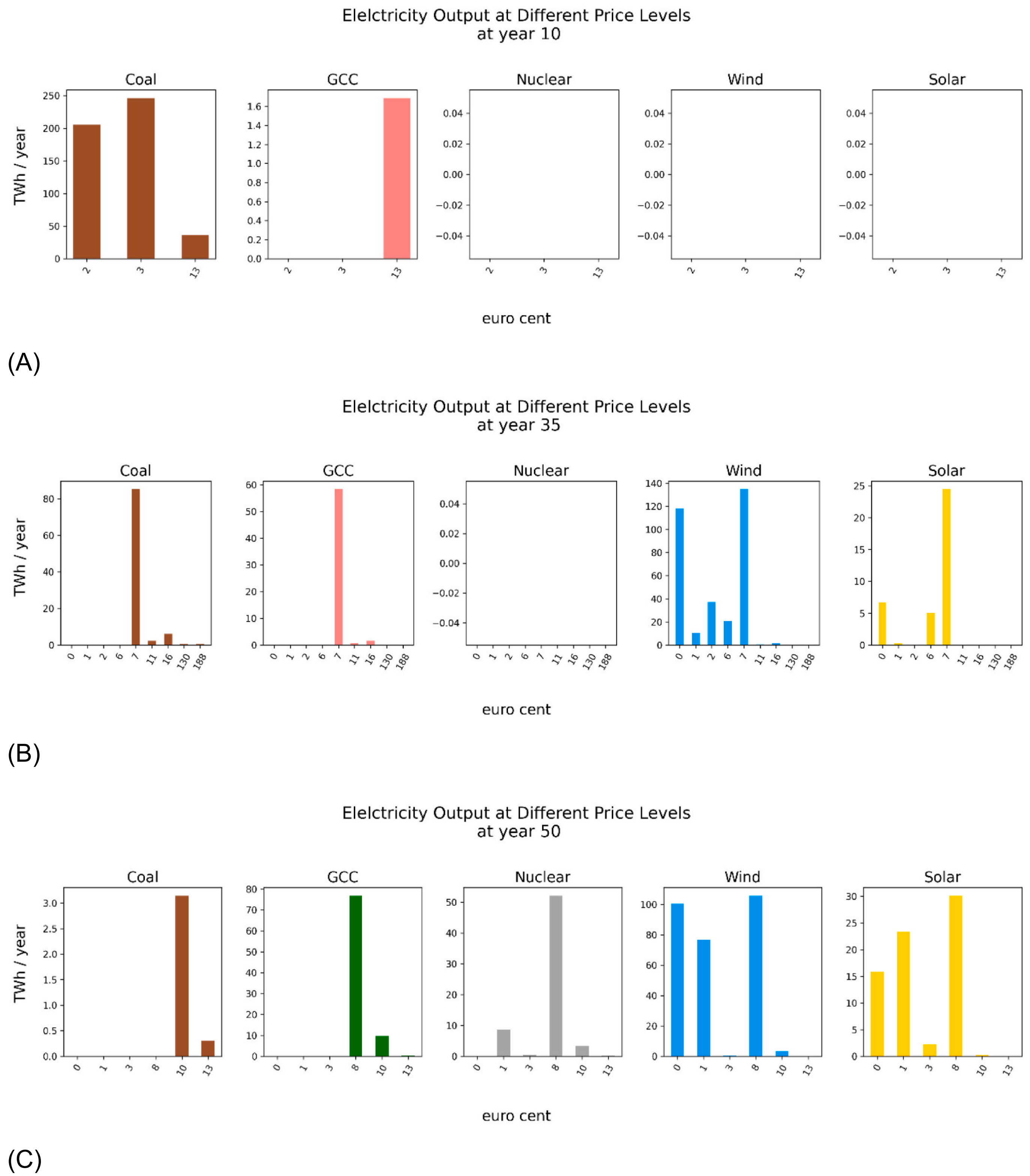
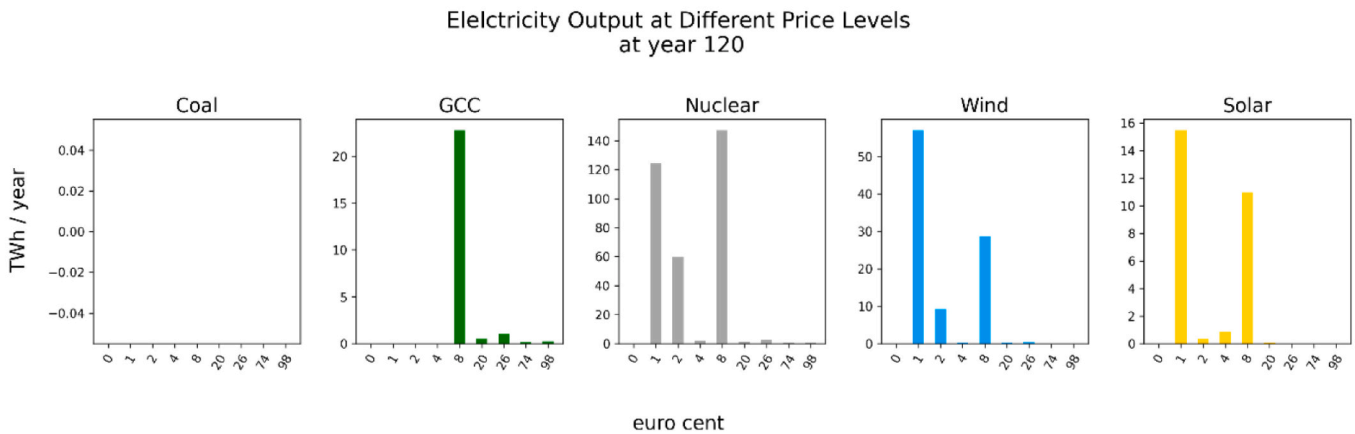


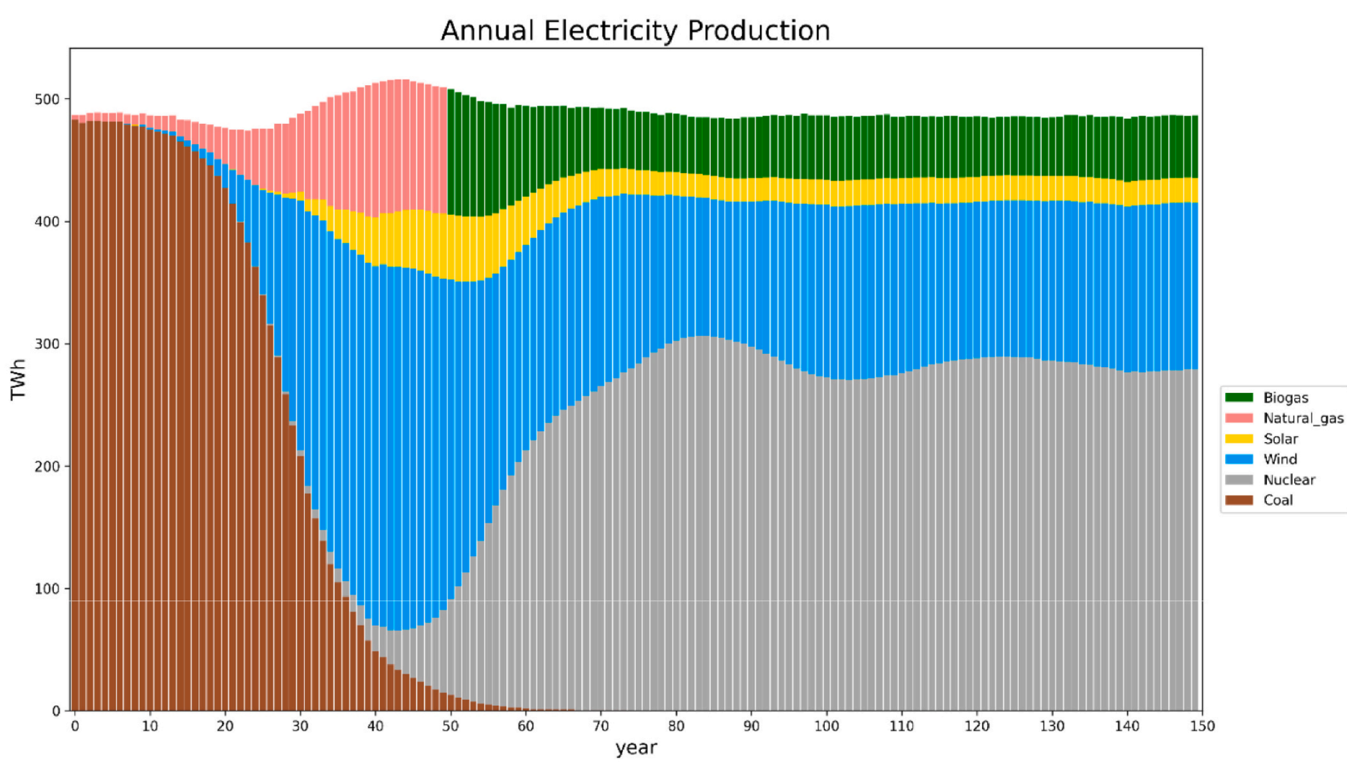
Fig. 7. Panel (A)-(D) shows the electricity production at different price levels in the adaptive case without stochastic processes. (A) year 10; (B) year 35; (b) year 50; and (D) year 120. Note that as the carbon price increases over time, coal and gas switch position in the merit order curve at year 32, as the marginal cost of coal, including the carbon price, becomes higher than that of natural gas. Panel (E) shows the development of the total annual electricity production from each technology over time.

electricity prices across various time intervals within a single year, exhibits an upward, although irregular, trajectory over time.

When comparing the adaptive and non-adaptive cases, it is evident that the adaptive case exhibits reduced volatility, especially after around year 50, as depicted in Fig. 9. This outcome can be attributed to the adaptive case's lower proportion of variable renewable energy



(D)



(E)

Fig. 7. (*continued*).

capacities, such as wind and solar, and a higher proportion of non-variable technologies, particularly nuclear power.

3.5. Agents' economic performances

In this section, we analyze individual agents' economic performances, measured by their equity over time and their bankruptcy rates in both the non-adaptive case and the adaptive case.

In the non-adaptive case, since all agents are homogeneous, they exhibit similar levels of equity (Fig. 10A) and bankruptcy rate (Fig. 11A). (Their bankruptcy rates are not identical due to limited simulation runs.)

In the adaptive case, a correlation can be observed between an agent's loss aversion level, equity value (Fig. 10B), and bankruptcy rate (Fig. 11B): lower levels of loss aversion are associated with higher average equity values and an increased likelihood of the agent facing bankruptcy. This highlights the trade-off between risk and return. As demonstrated in the previous section, less loss-averse agents make more investments (Fig. 4B), so they have higher average equity values, but also exhibit higher bankruptcy rates. Investment inherently involves varying degrees of risk. Given the uncertainties in future market and policy conditions, aggressive agents take on higher levels of risk than agents who adopt a more conservative investment strategy.

4. Summary of sensitivity analysis

In this section, we summarize the results of a sensitivity analysis examining the impact of three key elements in our model: (1) stochastic

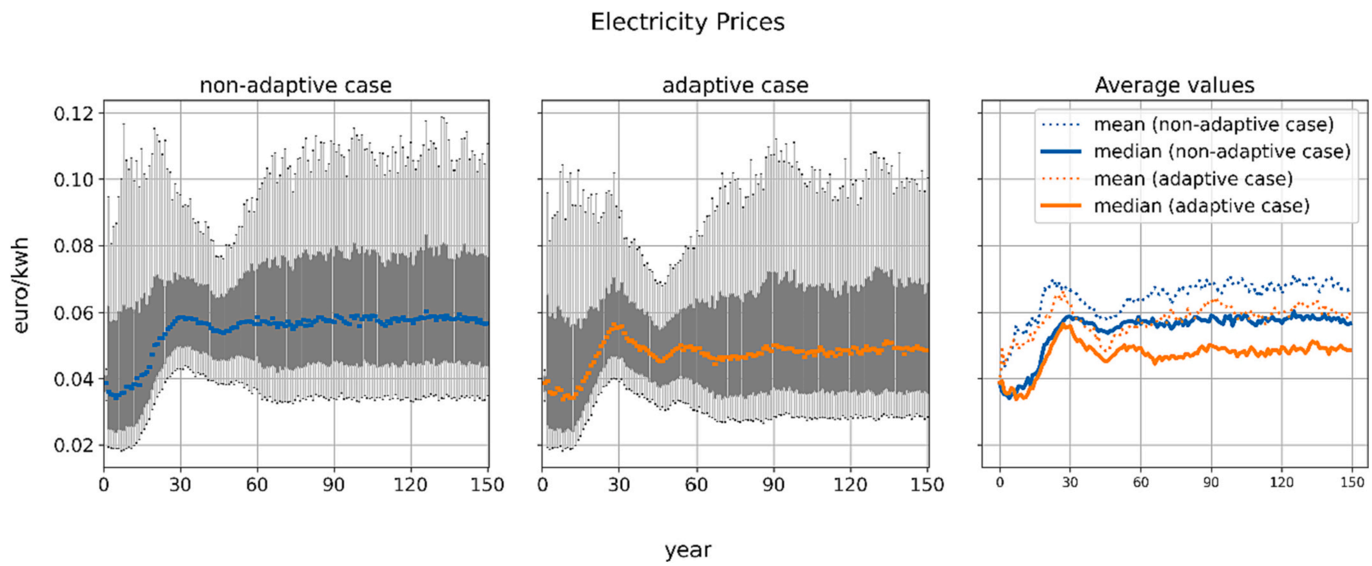


Fig. 8. A comparative analysis of average annual electricity prices for non-adaptive and adaptive scenarios, derived from the outcome of 1000 simulation runs. The first two panels exhibit the interquartile range (IQR) as the central dark grey region, spanning from the first quartile (Q1, 25th percentile) to the third quartile (Q3, 75th percentile), while the outer light grey regions signify the 10th and 90th percentiles. The median value is denoted by the solid line. In the third panel, both the mean and median values for the non-adaptive and adaptive cases are depicted.

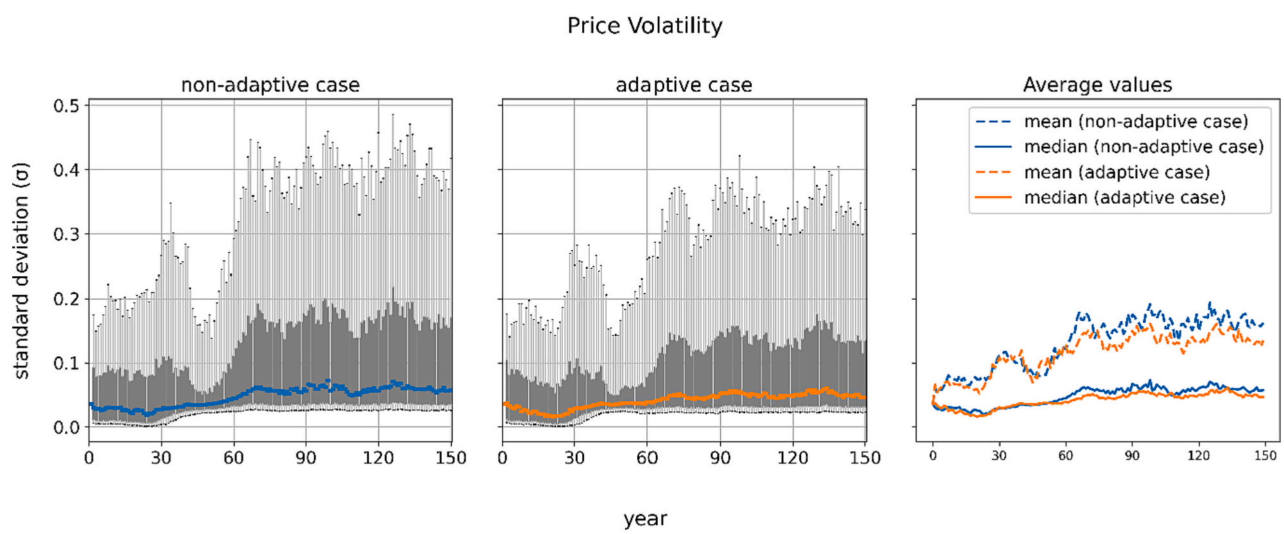


Fig. 9. The volatility (standard deviation) of electricity price within a year. The central dark grey region shows the first quartile (Q1, 25th percentile) to the third quartile (Q3, 75th percentile), while the light grey area signifies the 10th and 90th percentiles. The median value is denoted by the solid line. In the third panel, both the mean and median values for the non-adaptive and adaptive cases are depicted.

processes, (2) capital costs of nuclear power plants, and (3) forecasting methods for future carbon and fuel prices. For detailed analysis and figures, see section S3 in the supplementary material.

4.1. Stochastic processes

The analysis assessed the impact of the six stochastic processes as detailed in Section 2.2, such as fuel prices, carbon prices and electricity demand. To evaluate the influence of each, we hold it constant in individual sensitivity analysis, producing six distinct scenarios. The results showed that when natural gas and biogas prices are constant, there are fewer GCC plants but increased nuclear, wind, and solar capacities. This change underscores the influence of fluctuating gas prices on energy investments. Furthermore, scenarios with non-variable electricity demand exhibited both reduced electricity price volatility as well as smaller variations in investment amounts among different participants, revealing the important role demand plays in setting electricity prices and investment decisions. Financially, agents faced different bankruptcy rates based on the fluctuations of fuel prices and electricity demand, highlighting the intricate interplay between price stability and financial outcomes in the model.

We also tested a scenario where the average fuel price for gases and nuclear are increasing over time. Results show that there are notable changes in the energy mix. Specifically, we observed a decrease in the investment in gas-fired and nuclear power plants (as expected) and an increase in wind and solar installations.

4.2. Capital cost of nuclear power plants

The cost of nuclear power plants is pivotal for energy investment decisions. We explore both lower and higher assumptions in the sensitivity analysis. We find that lower nuclear costs accelerate and increase

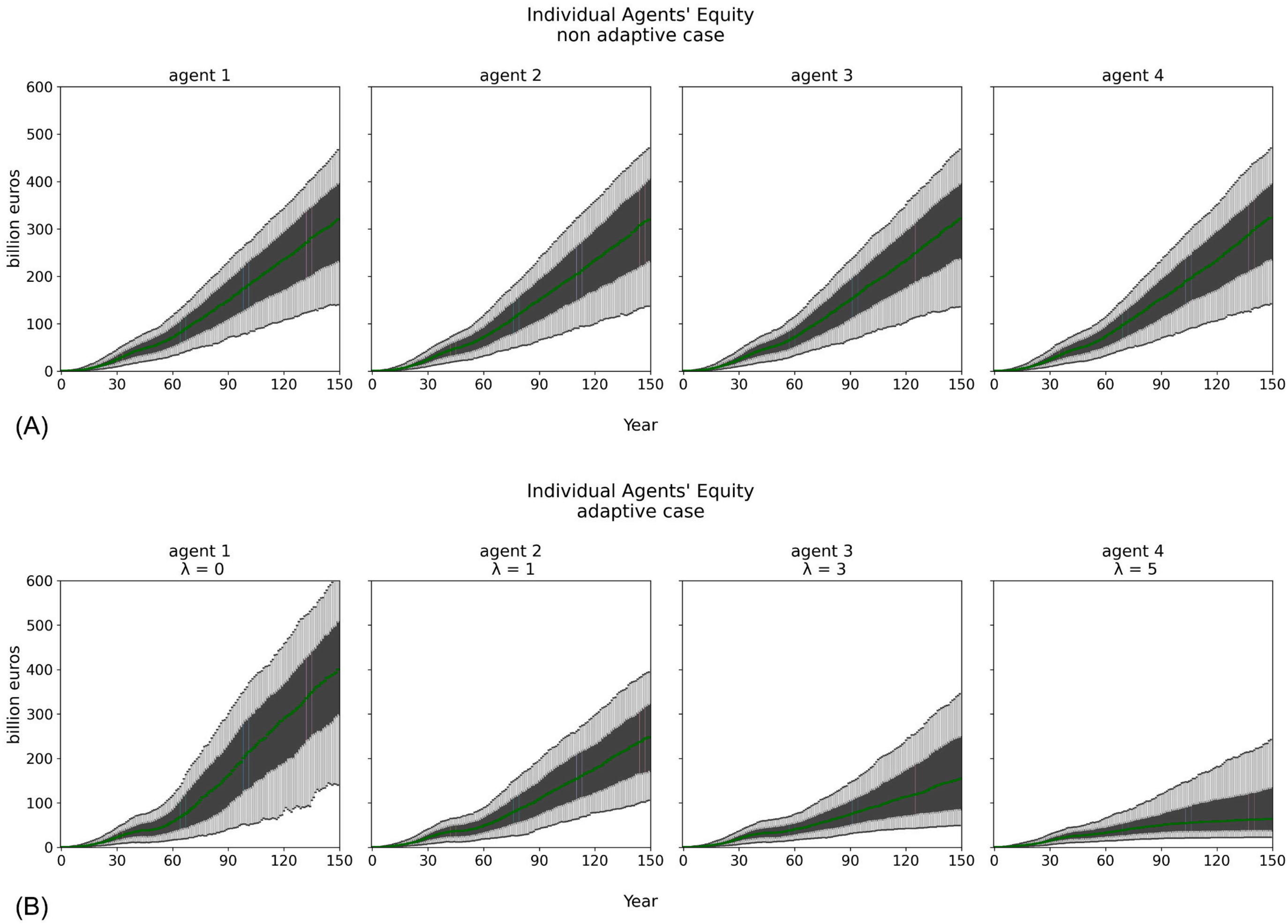


Fig. 10. Individual agents' equity value over time. (A) non-adaptive case; (B) adaptive case. The results are from 1000 simulation runs. The central dark grey region shows the first quartile (Q1, 25th percentile) to the third quartile (Q3, 75th percentile), while the outer lighter grey area signifies the 10th and 90th percentiles.

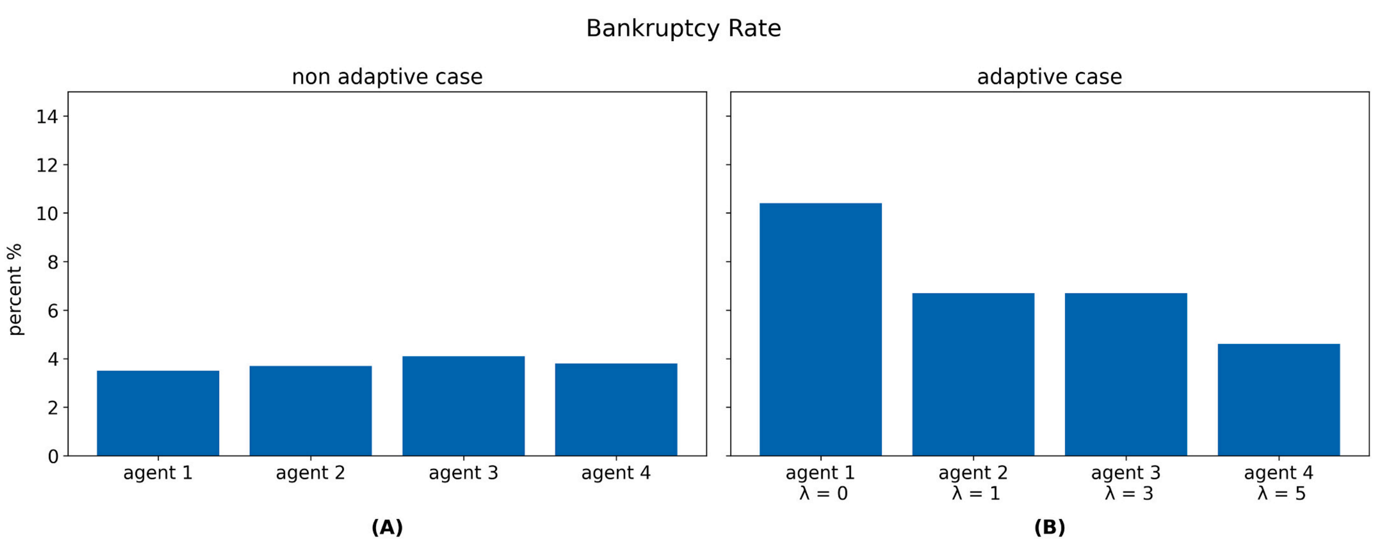


Fig. 11. Bankruptcy rate for each agent in the non-adaptive case (panel A) and the adaptive case (panel B). The results are based on 1000 simulation runs.

nuclear investments, whereas higher costs delay and reduce them, making investments unlikely beyond 9000 Euros per kW. Electricity prices corresponded proportionally to nuclear capital costs: cheaper nuclear led to lower electricity prices and vice versa. Additionally, price volatility is reduced with cheaper nuclear due to their stable production. When nuclear costs are higher, coal's hurdle rate is lower, delaying its phase-out.

4.3. Forecasting method

In one test case, agents forecast future fuel and carbon prices by extrapolating trends from the past five years' data instead of taking the average of the past five years. Although installed capacities in this scenario were largely consistent with the reference case, the first 60-year period exhibited an increase in GCC capacity and decreases in wind and solar capacities. These changes were driven by the expectation of future gas price reductions in cases where the trend where negative. Financially, this forecasting method increases the risk of bankruptcy. This risk increases because the extrapolation-based forecast does not align well with the model's intrinsic stochastic price fluctuations, which revert to an average price (or price trend in the case of the CO_2 price).

5. Conclusion

The electricity generation landscape has experienced a significant transformation in recent years, marked by unparalleled growth in the use of renewable energy sources [40]. The pivotal role of investors in this transition is crucial; their financial contributions are the necessary capital for the deployment of these renewable technologies.

Investors, however, contend with substantial uncertainties and risks when deciding which technology to invest in. These uncertainties stem from a myriad of unpredictable elements like fluctuating electricity demand, technology performance, variable market conditions, and evolving policy landscapes. In such an uncertain investment environment, investors strategically adapt their decisions to align with the prevailing circumstances. This propensity for adaptive decision-making can either expedite or impede the transition towards a low-carbon electricity system, a factor often overlooked in most energy system models.

This research endeavors to contribute to the existing literature by developing the depiction of companies' adaptive investment decisions in energy system models, utilizing a novel agent-based model. The model captures investment decisions under uncertain conditions, factoring in changes to hurdle rates that are influenced by the financial performances specific to each technology, and the different levels of loss aversion among investors. Moreover, our study sheds light on the impact of companies' adaptive behaviors both on their investment choices and on the transition towards a low-carbon electricity system. There are three main findings from this study.

Firstly, our model results indicate that when agents display adaptive behavior, they tend to invest more significantly in profitable technologies compared to non-adaptive agents. In the context of this study, this leads to increased investment in wind and solar during the early transition phase (approximately from year 20 to year 60 in the model) and an increase in nuclear investments later in the transition phase. The reason for this lies in the adaptive hurdle rate employed by agents. When a technology becomes competitive, agents respond by reducing the hurdle rate for that technology, thereby giving incentives to further investments.

Secondly, our study reveals that when agents are adaptive, the average electricity price and its volatility generally tend to be lower compared to the scenario with non-adaptive agents. This can be attributed to the lower hurdle rate applied by the dominant agents and larger investments made in the adaptive case.

Thirdly, our study also uncovers those adaptive agents, depending on their degree of loss aversion, adjust their hurdle rates differently and consequently make distinct investment choices. Agents who are less averse to losses tend to invest more, whereas those who have a higher aversion to losses tend to invest less. Moreover, a lower level of loss aversion generally corresponds to a higher equity value but also results in a higher bankruptcy rate. This finding underlines the inherent trade-off between risk and returns.

In summary, the contribution of this study is two-fold. Firstly, this research contributes to energy system modeling practice through the introduction of a novel agent-based model. This model accounts for the complexities of investment decision-making, including adaptiveness, risk aversion, and the uncertainties inherent in the electricity system. This innovative modeling tool effectively encapsulates the dynamic interplay among investment decisions, technology performances, and market conditions. It thus offers an alternative depiction of investment decisions and the complexities involved in energy transitions.

Secondly, using this model, we conducted a comprehensive analysis of key aspects of the electricity system in the context of low-carbon transition. This includes examining the development of generation capacity mix, electricity prices, and the profitability of various technologies and investors. We believe that this work can strengthen the utility of energy system models in aiding decision-making processes and promote more effective decisions in the shift towards a low-carbon energy future.

CRediT authorship contribution statement

Jinxi Yang: Conceptualization, Methodology, Investigation, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Validation. **Daniel J.A. Johansson:** Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link of the data and the model code in the manuscript.

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Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.apenergy.2023.122603.

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