



# How can energy system models align with the real-world tragedy of the horizon? The impact of decision-makers' short-term biases and temporally-inconsistent preferences

Diamantis Koutsandreas<sup>a, b, \*</sup> , Ilkka Keppo<sup>a</sup> 

<sup>a</sup> Department of Energy and Mechanical Engineering, Aalto University, Otakaari 4, 02150 Espoo, Finland

<sup>b</sup> Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Potsdam, Germany

## HIGHLIGHTS

- We introduce a temporal inconsistency framework for energy system modeling.
- Optimal decisions made for the future change depending on when they are made.
- We apply this framework to assess mitigation scenarios for Greece's power sector.
- Results indicate profound impacts of short-term biases and temporal inconsistencies.
- These mainly include increased system costs and lock-ins to sub-optimal pathways.

## ARTICLE INFO

### Keywords:

Myopic foresight  
Social discount rates  
Time inconsistency  
Temporal preferences  
Power sector

## ABSTRACT

Decision makers often operate on short-term horizons, placing more weight on the short term and revising their decisions later as new information arises. What's more, literature has shown that the implicit discount rate at which decisions are made for the future isn't constant, but changes as a function of the point in the future for which the decision is made. While the myopic foresight of decision makers has been extensively studied in the energy system modeling literature, the focus has been on a binary representation in which time periods beyond the defined decision horizon are completely ignored, and changes in strategies are a result of new information, rather than different valuation of a specific future cost. This study introduces a temporal inconsistency framework for energy system modeling. In this approach, decision-makers do plan for the full time horizon, but assess future value based on a changing discount rate and, as time is moved forward, reassess this value at each one year step. This approach advances the state of the art by simulating temporally-inconsistent decision making, in which optimal decision made for a given year changes as a function of when those plans were made. We demonstrate this framework by simulating decarbonization scenarios for the Greek power sector with varying levels of path dependency and commitment over 2019–2070. The results highlight that logarithmic discounting can lead to irreversible sub-optimal pathways, whereas exponential discounting produces sub-optimal early decisions, which however can later be revised, moving closer to the time-consistent pathway (up to 10 times less natural gas-fired power generation in 2050 compared to initial plans).

## 1. Introduction

### 1.1. Problem setting

Energy system optimization models (ESOMs) typically assume a long-term, perfect-foresight approach, in order to identify “optimal” pathways across all time steps of the modeling horizon [5]. The objective function of such models is to minimize total discounted system costs,

while considering other policy considerations (e.g., emissions and land use) as model constraints or additional cost factors. In that framework, a constant social discount rate is typically assumed, reflecting the equitable way of distributing the costs of the transition between current and future generations [19,36].

The artifact of perfect foresight assumes a unique (i.e., no-actor preferences), rational (i.e., minimizes system costs) social planner who has

\* Corresponding author at: Department of Energy and Mechanical Engineering, Aalto University, Otakaari 4, 02150 Espoo, Finland.

Email address: [diamantis.koutsandreas@aalto.fi](mailto:diamantis.koutsandreas@aalto.fi) (D. Koutsandreas).

apriori knowledge of how the future will unfold, including the impacts of their decisions on subsequent years within the anticipated time horizon [17,35]. This implies that there is a single, fixed instance of input data across the examined time framework, as if the implied system planner had perfect knowledge about the future evolution of input data already from the base year. Consequently, in perfect foresight with consistent (i.e., fixed) discounting, the sequence of optimal decisions is not affected by the timing of decision making: a decision made under this framework for a given time period will remain optimal, no matter at which point in time the decision was made. That said, if a technology portfolio plan is crafted in 2025 for the period until 2070 and is followed, there will be no point in revising the plan later (e.g., 2030) as the optimal decision will be exactly the same.

However, as discussed below, this setting clearly diverges from real-world decision making in many respects [13]. Consequently, while providing valuable insights into optimal investment decisions under the given assumptions, this approach doesn't accurately capture many of the elements of the real-world decision making driving the development of the energy system. This discrepancy helps explain why actual system developments deviate substantially from pathways formulated based on cost optimization [34].

The tendency of decision makers to prioritize the short-term costs of their choices due to other interests [4] is particularly relevant in politics, where decisions are usually made within a political horizon—typically spanning between 4 to 8 years—the so-called phenomenon “tragedy of the horizon” [30]. Consequently, decision makers often operate on shorter time horizons, thereby committing to short-term actions and adjusting their strategies based on new information or changing conditions [2,12,29]. As noted, the balancing of current and future costs, and thus also the potential preference for short-term gains, can be incorporated into ESOMs through the constant rate used for discounting costs. This parameter is typically called social discount rate and is defined at a fixed rate across the whole modeling horizon, denoting how future system costs are devalued to present terms. This setting allows for evaluating the present value of an energy system pathway's costs [6,14], and the value for the rate is typically derived to reflect inter-generational justice, although there are varying views about what the value should be [28].

Real-world decision makers' preferences, however, exhibit dynamic inconsistency, so that what is considered an optimal decision depends on how far the decision maker is from the period for which the decision is made. This attitude implies changing discount rates over time [7]. Moreover, system planners tend to update their investment decisions in response to new information, such as changes in technology costs, fuel prices, demand projections, regulatory frameworks, macro-economic conditions, and policy environments. Furthermore, it's worth noting that utilities may not be susceptible to inconsistent discounting; such behavior is more commonly associated with individuals (e.g., policy makers), who may also face relevant objectives (e.g., political costs) and tendencies (e.g., behavioral distortions) to do so. This is why we frame our analysis from the perspective of system planning, i.e., as if a social planner were in charge of making forward-looking investment decisions for the whole system.

## 1.2. Literature overview

The aspects of discount rates and sequential decision making with myopic foresight have received some attention in the existing body of energy system analysis literature. In the standard setting, when perfect foresight is assumed, the full time frame of the analysis is considered simultaneously and the cost burden across time periods is defined based on the social discount rate. As noted, this rate can be defined in a number of ways, such as using the interest rate of government bonds [31] or the growth rate of real per capita income [26] as proxies. A commonly used rate is 3.5%, which is argued to be a “fair” value from a societal perspective [8], but — as noted — views differ, and rates close to zero

have also been used. A body of the literature has examined the impact of different discount rates, reflecting how much of the burden is pushed to future generations.

García-Gusano et al. [11], for example, employed two ESOMs—ETSAP-TIAM and TIMES-Norway—to evaluate the impact of different discount rates on model results, considering both social- and technology-specific hurdle rates. For the latter, they also considered scenarios with varying discount rates over time, ranging from 1% to 2% over a 20-year period. Their findings pinpointed that lower social discount rates are associated with higher shares of renewable technologies in the power mix, and also that hurdle rates can, to some extent, counteract this development. They didn't, however, investigate time-varying social discount rates, or temporal inconsistencies in them.

In addition to social discount rates, myopic foresight is an alternative way of modeling short-term bias: the future is considered only until a given point, beyond which it doesn't influence decision making. Indicatively, Fuso Nerini et al. [9] employed a myopic foresight version of the UK TIMES energy system model (My-UKTM) to assess the implications of myopic foresight on the transformation of the UK's energy system. Using this model, they identified cost-optimal energy system pathways for 30-, 20-, and 10-year time moving decision windows. Their findings highlighted that myopic foresight can lead to delayed investments in renewable energy technologies, thereby resulting in higher system costs over the examined period. In this setting, however, Keppo and Strubegger [18] developed and used a limited foresight version of the MESSAGE energy system model, in which the outcome is also driven by the new information that is being revealed, rather than stronger devaluation — or temporal inconsistencies — regarding the future costs.<sup>1</sup> Martinsen et al. [24], in turn, utilized the IKARUS model [25]—a dynamic linear optimization model with a five year decision window—to evaluate the implications of scenarios involving steadily increasing prices and a sudden price shock, against a moderate price scenario. Their results indicated that high prices could expedite the transition of the energy supply to renewable energy sources, but they provided few conclusions about the impact of the foresight itself, as there was no perfect foresight version of the model. Also, and similar to all other myopic studies, they didn't investigate the impact of temporal inconsistencies in the discounting.

Extending the scope beyond energy system analysis, a critical body of literature has also examined the implications of distorted valuation or foresight on energy transitions, such as those caused by differentiated or time-varying discount rates. For instance, Heinzl and Winkler [15] explored the welfare consequences of divergent social and private time preferences when transitioning from fossil fuel-powered to clean energy technologies, employing a time-lagged general equilibrium model. Their findings revealed that distorted time preferences could result in delayed investments in clean energy technologies, potentially impeding the energy system's transition.

Similarly, Chiappinelli and May [3] employed a dynamic regulation game focused on renewable energy to explore the circumstances that can incentivize governments to backtrack on their commitments, and then assessed the ramifications of different support policy regimes and deployment targets on compliance. They applied this framework to the Spanish and German energy systems over the 2010–2013 period. Their findings indicated that the primary drivers behind renewable energy developments in these countries were the emission intensity of the conventional power plant fleet, regulatory shortsightedness, and prioritization of supporting policy costs for consumers over producer benefits. More generally, there is an extensive literature stream in behavioral

<sup>1</sup> Although one can interpret the time periods not included in a specific myopic decision window to be discounted with an infinite discount rate, thus not affecting the optimal results. As these time periods later then do enter a decision window in which the normal social discount rate is used, one could also interpret this as a specific, somewhat binary implementation of temporal inconsistency.

economics concerning present-bias preferences (e.g., Augenblick et al. [1]), but few applications exist in the sphere of energy system analysis and modeling.

### 1.3. Research gap and paper's contribution

The preceding body of literature has provided valuable insights into the impact of discount rates and myopic foresight on the sustainable transformation of energy systems, highlighting potential delays, increased costs, lock-in effects, and potentially higher emissions. This paper builds upon these studies, focusing on investigating within an energy system modeling framework the potential impacts of time inconsistency. Specifically, prior studies have either focused on the impacts of myopic foresight, or on time-consistent impacts of discount rate changes. As discussed, while both of these can, in their own ways, reflect present-bias in the decision making — myopic formulations by completely ignoring future needs and discount rate sensitivity studies by increasing the relative costs of today against future costs — neither of them is capable of capturing the empirically observed way in which this bias can lead to temporally inconsistent decision making.

This study aims to advance the modeling by explicitly considering short-term bias and temporal inconsistency. This is done by introducing discount rate curves with increasing values into the model, to denote different approaches concerning how short-term-focused social planners may discount the future and using a sequential decision-making process with a rolling one-year forward-looking window, in which the discount rate curve moves with the decision making period. For the discount rate, we use two illustrative discount rate curves, one exponential and one logarithmic. We don't argue that either of these curves is likely to represent the way in which actual decision makers make decisions, but they capture two key elements of it: the temporal inconsistency and present bias. The use of two curves also allows us to assess the sensitivity of the latter, as the logarithmic curve reaches high social discounts very rapidly, effectively leading to discount factor values close to zero for periods further in the future. As breaking hard constraints, such as climate targets, would imply infinite costs, however, the implied decision maker will not make decisions that make reaching the long-term target infeasible.

For the sequential decision making, at each step the implied social planner assesses all future years, makes a decision for all of them, and the time is moved one year further into the future. At the next step, past decisions are fixed, but new plans can be drawn for all the future years. The moment of "right now" moves with time, and so do the related discount rate curves, introducing an element of time inconsistency to the modeling: a result deemed optimal for a future year may no longer be such for a later decision-making year. The analysis thus allows also differentiating between the multiple plans and final decisions made for each year in the model horizon, with the final trajectory of the system consisting of the latter.

Although assuming perfect foresight in each time step, our framework reflects the emergence of new information in the planning process, which necessitates revisions of planning decisions. This occurs in two main ways. First, under the chosen discount-rate specifications, the implied social planner becomes effectively myopic after a certain number of years, as the discount factor approaches zero. In each time step, the effective decision horizon moves further into the future, allowing social planners to see further ahead. Second, by changing time preferences in each step, social planners are implicitly faced with different information for the same future years. That is, as the discounting for a given future year changes, its discounted value from today's perspective also changes. For example, this implies a different present value of technology costs and carbon prices for the same future year.

The remainder of this paper is structured as follows. Section 2 outlines the adopted methodology to evaluate the impact of short-term bias and time inconsistency on power system transformation. Section 3 presents the main results arising from applying this methodology

to the decarbonization of the Greek power sector, with a focus on the discrepancies across different intertemporal investment decisions. Finally, Section 4 concludes the paper and proposes potential avenues for future research in the examined field.

## 2. Methodology

### 2.1. Modeling framework

This paper introduces the dynamic-recursive, time-inconsistent version of OSeMOSYS-Greece, which is available on GitHub<sup>2</sup> OSeMOSYS-Greece is an implementation of the Open Source energy MODelling SYStem (OSeMOSYS) framework, designed and parameterized to represent the modus operandi of the Greek power sector (a detailed documentation of the model is available in [20–23]). The model computes annually the cost-optimal combination of power-producing technologies, including capacity investment and usage to meet the exogenously defined electricity demand, while also adhering to the constraints set in the model (e.g., mitigation targets, resource and technology constraints). In its standard form, it applies a deterministic linear programming optimization, assuming no actor-specific preferences or behaviors, perfect foresight, and economically-rational decision making.

The objective function of the model minimizes the total discounted system costs, as reflected in Eq. (1).

$$\min \sum_{y=y_0}^Y \sum_T \left[ \underbrace{\frac{NC_{T,y} \cdot CC_{T,y}}{(1+r_y)^{y-y_0}}}_{\text{Investment costs}} + \underbrace{\frac{TC_{T,y} \cdot FC_{T,y} + \sum_l (A_{l,T,y} \cdot YS_{l,y} \cdot VC_{T,y} + E_{l,T,y} \cdot EP_y) - SV_{T,y}}{(1+r_y)^{y-y_0+0.5}}}_{\text{Operational costs}} \right] \quad (1)$$

where  $y_0$  denotes the base year of the modeling horizon (i.e., 2019) and  $Y$  reflects the final model year (i.e., 2070). Investment costs for technology  $T$  in model year  $y$  are calculated as the product of newly installed capacity  $NC_{T,y}$  (in GW) and the corresponding capital cost per unit of capacity  $CC_{T,y}$  (in \$ million per GW). Fixed operating costs are computed as the product of the total available capacity  $TC_{T,y}$  (in GW) of technology  $T$  and the fixed operation and maintenance cost  $FC_{T,y}$  (in \$ million per GW). Variable operating and emissions-related costs are calculated over intra-annual time slices by multiplying the activity level  $A_{l,T,y}$  of technology  $T$  in time slice  $l$  and year  $y$  (in PJ) by the year-split parameter  $YS_{l,y}$  (representing the share of time slice  $l$  in a full year) and the variable unit cost of activity  $VC_{T,y}$  (in \$ million per PJ). Emissions from technology  $T$  in time slice  $l$  and year  $y$  (in Mt), denoted by  $E_{l,T,y}$ , are multiplied by the emissions penalty  $EP_y$  (in \$ per Mt). The term  $SV_{T,y}$  represents the salvage value of the remaining capacity of technology  $T$  attributed to year  $y$  and is treated as a revenue. The term  $r_y$  denotes the discount rate applied in year  $y$ , which varies according to the temporal distance between  $y$  and  $y_0$ . Investment costs are discounted to the beginning of  $y_0$ , while all other cost components are discounted to the middle of each year (reflecting that they accrue throughout the year).

Based on the discount rate attributed to year  $y$ , a discount factor  $DF_y$  is derived, reflecting the rate at which costs incurred in that year are discounted to base year (i.e., how important they are from base year's perspective), as shown in Eq. (2).

$$DF_y = \frac{1}{(1+r_y)^{y-y_0}} \quad (2)$$

<sup>2</sup> Available at <https://github.com/daymontas1/DR-Myopic-OSeMOSYS-Greece.git>.

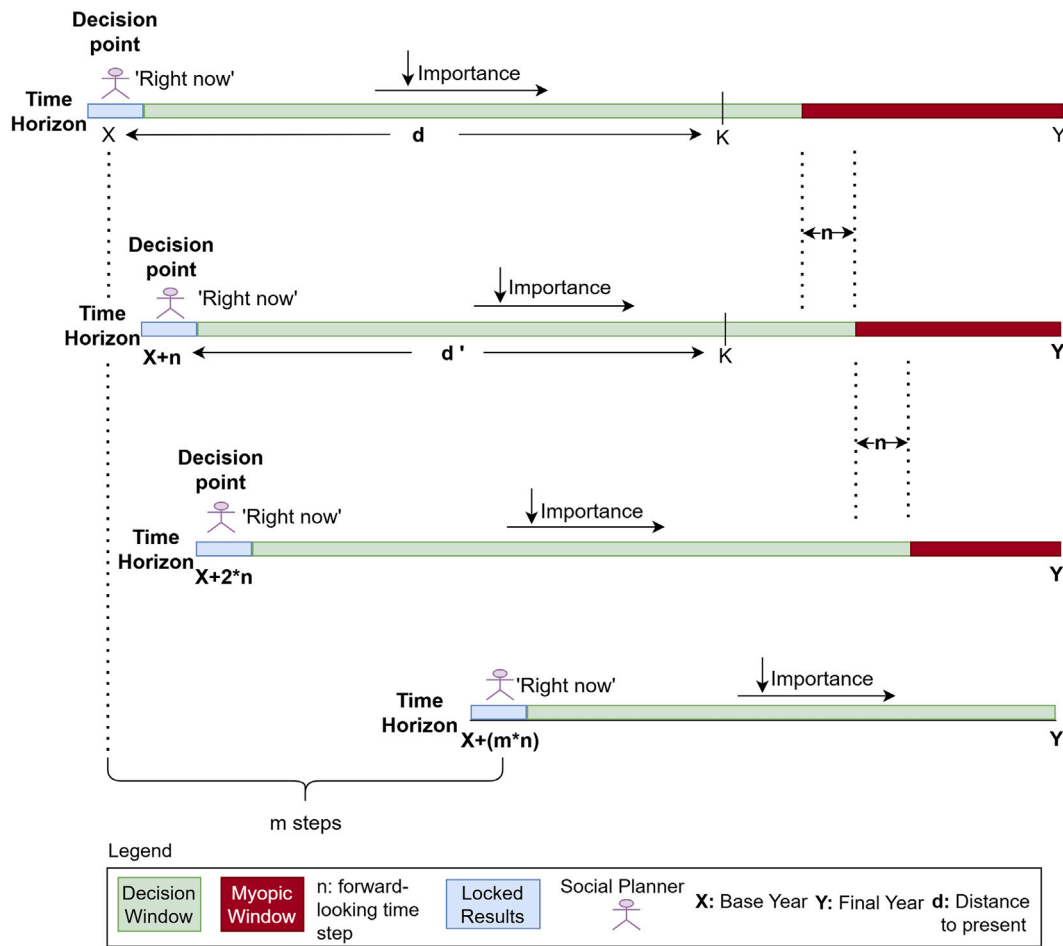


Fig. 1. Adopted conceptual framework for modeling temporal inconsistency in energy system planning. “X” and “Y” represent the base and final years of the modeling horizon, respectively, while “n” denotes the length of the forward-looking time step for planning revision. “X + n” represents the year lying “n” years after the base year “X”. Each line reflects a planning decision made at a given point in time (X, X + n, X + 2\*n, X + (m\*n)).

Considering varying discount rates depending on the time of decision allows studying the short-term bias and temporal inconsistency of decision makers. The basic concept of this approach is illustrated in Fig. 1. Specifically, the adopted methodology involves a consecutive decision-making process with a rolling forward-looking window that is moved forward  $n$  years at each step (Fig. 1). For each run, the implied social planner reassesses future investment decisions from a standpoint in time that is  $n$  years further in the future than for the previous run ( $y'_0 = y_0 + n$ ). A discount rate curve in which the rate increases over time is used, with the start of the curve moving with the decision maker ( $r(y'_0) = r(y_0)$ ). This means that the decision maker will always use the same discount rate for a year that is  $n$  years in the future (and only for that year), but the year that is  $n$  years in the future changes at each step. Consequently, in each step, the implied social planner is tasked with solving a different optimization problem, which results in variability in decisions for the same years depending on how close/far to those years the decision is made.

This method contrasts the conventional energy system modeling approach that anchors decision makers to the base year of the analysis, and the myopic approaches that discount the visible future with a constant rate (and completely ignore the future beyond the decision window). This leads to the optimal decisions for a given future year to keep changing as the decision maker moves closer to that year, as it starts to become more and more important for them. It should be noted, however, that although our approach reflects myopic foresight, this occurs only partially: even when the discount factor approaches zero beyond a certain time point, the social planner may

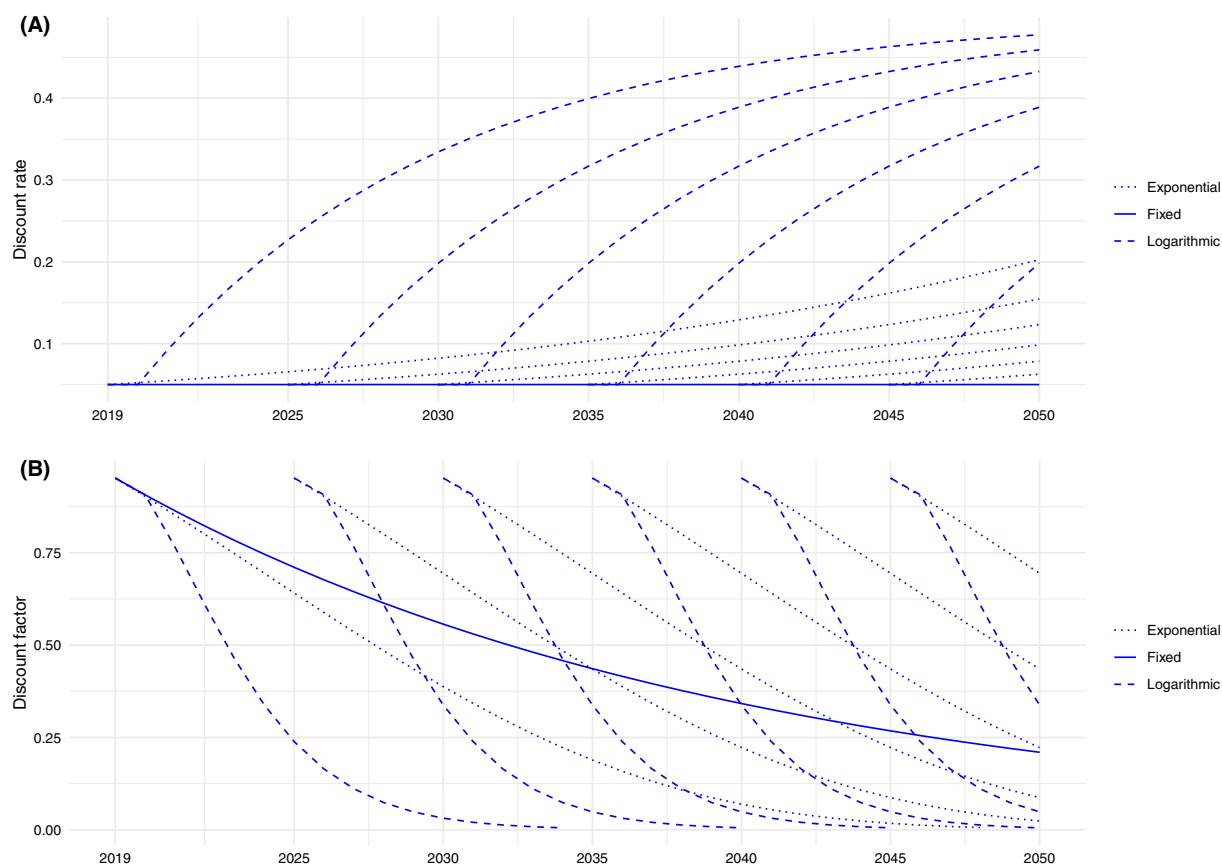
still see model infeasibilities, thereby factoring in that period in their decisions.

At each step, the model computes the cost-optimal power mix with perfect foresight, taking into consideration the changing discount rates (see above for details). Previous decisions are irreversible (Fig. 1) and affect those that come after through e.g., installed technology capacities, growth constraints, and the remaining emission budget. The model is implemented in MathProg, while R scripts are used to update the input files for each run.

## 2.2. Scenario design

We first establish a conventional, time-consistent mitigation pathway on which our other, time-inconsistent scenarios are developed. We use a fixed discount rate of 5% for this scenario, perfect foresight, and include in the modeling the Greek government’s official targets for the power sector, as outlined in the initial version of its National Energy and Climate Plan (NECP) [16]. These targets primarily refer to (1) the renewable technologies’ share in the power mix in 2030 (i.e., 65%), (2) the phase out of lignite power plants by 2023 (except “Ptolemaida V”, phased out by 2028), (3) the integration of non-interconnected islands into the main grid by 2030, and (4) system decarbonization by 2050. The model has the flexibility to decide the trajectory of the system between the applied year-specific targets, based on a cost-minimization rationale.

The results from this initial simulation are used to build two scenarios in which mitigation targets for the power sector are considered



**Fig. 2.** Logarithmic and exponential discount rate curves assumed in the study to reflect on how real-world's decision makers may value the future while moving forward (Panel A) and the resulting discount factor curves (Panel B). The process of positioning discount rates into the future is illustrated indicatively for different base years within the examined modeling horizon. Higher discount rates, and conversely lower discount factors, in future years indicate that decision makers attribute less importance to the consequences (i.e., system costs) in those years compared to earlier years.

in alternative ways. The first scenario, “Carbon Price Scenario” (CPS) hereinafter, uses carbon prices to achieve mitigation targets. The price trajectory is derived through the following sequence of actions: (1) taking the emission path of the initial, time-consistent simulation; (2) implementing this path as an annual emissions cap in the model and re-running the simulation with this constraint; (3) deriving the resulting dual prices of the emissions constraint and using them as carbon prices. This procedure allows us to observe how much the model may deviate from the original emission path, now that it has the flexibility to do so. For our other policy scenario setup, marked as “Carbon Budget Scenario” (CBS), we use the cumulative emissions of the first, time-consistent, run as an emission budget, allowing the model to decide how to distribute it across the time periods. It should be noted that in both scenarios, the only constraint that remains in place from the original setup is the phase out of lignite plants. This is done to guide the model toward a direction that may not have been taken by implementing carbon prices or carbon budget alone.

The two scenarios are used to investigate the different ways in which the introduction of time inconsistency may affect decisions made for mitigation and power sector configuration. Fundamentally, they differ in terms of the flexibility they allow, i.e., “soft constraints” in the form of carbon prices or “hard constraints” in the form of a carbon budget. With prices, the decision makers can make decisions that lead to more or less mitigation throughout the full time horizon, whereas with a carbon budget only the timing of the mitigation can be adjusted. It's worth noting that in the real world, policy makers would have an option to renege on the commitments made by past policy makers, whereas here not reaching the carbon budget implies infinite costs.

We then implement our time-inconsistent framework for both CPS and CBS, which includes a consecutive decision making (see details above). We assume for all runs a one-year time step and a forward-looking window until the end of the modeling horizon. For both policy implementations, we analyze two differently shaped discount rate curves, a logarithmic and an exponential one, depicted in Panel A of Fig. 2. Each curve signifies a distinct way in which the implied social planner in the model envisions and values the future, with clear differences between the two. In particular, with a logarithmic curve, the discount rate jumps very high very quickly, but the growth in the rate then slows down. Conversely, under the exponential curve, the rate grows more slowly, but the growth keeps increasing the further we look. It's worth noting that final decisions are always made with the same low rate, and the future rates only affect the planning for the future years (which, in turn, affects also the decisions for today).

It's worth noting that, if we were to empirically estimate the discount rate curves that best describe energy planning investment behavior in Greece, we would need to compare least-cost pathways from past studies that used perfect foresight with consistent discounting against historical developments observed in the Greek power sector. In turn, we would have to rerun the models using alternative discount rate curves to determine which specification most closely reproduces observed outcomes. Given that the models used in these past studies are not publicly available, we would need to conduct this exercise with our modeling framework, extrapolating its base year back into the past. However, such an exercise would go beyond the scope of our analysis. This is also because when it comes to individuals, there is no single empirically established discounting behavior, and in practice different forms

of discounting may arise depending on the actors in charge of making energy planning decisions. Consequently, even if we were to empirically estimate the discount rate curves, this wouldn't necessarily imply that future decision makers in Greece would exhibit similar discounting behavior.

For this reason, we employ two widely used discounting specifications in economics—exponential and logarithmic discounting—to explore the sensitivity of results to alternative intertemporal preference structures. As noted previously, we do not suggest that actual decision making would follow either of the curves, that a specific parametrization of the curves would be better than another, or that one type of curve is more likely than another. Rather, our aim is to assess how temporal inconsistency in the modeling setup may affect results, in turn analyzing the sensitivity of results to alternative discounting assumptions.

Based on these discount rate curves, the corresponding discount factor curves can be drawn, as depicted in Panel B of Fig. 2. When the discount factor approaches zero—as happens in the case of the logarithmic and exponential discount rate curves in around a 15-year and 30-year horizon, respectively—decision makers no longer consider the cost implications of their current decisions beyond that point, except insofar as they must avoid infeasibilities (which carry an implicit infinite cost in linear optimization). It's worth noting that in the scenario with carbon prices, the undiscounted carbon price path is derived from the initial run and does not change, although the different discount rates mean that their present values now differ from the initial run. This assumption can be interpreted as the implied policy maker in the model using standard social discounting, and a fixed discount rate, for planning the appropriate and intergenerationally fair carbon price trajectory, but then using a different valuation of the future for the actual decision making.

The consecutive one-year rolling forward-looking window is applied from 2019 to 2050, while the final year of the modeling horizon is set to 2070 to avoid end-of-horizon, knife-edge effects. This means that the final run of the iteration covers the 2050–2070 period, and produces the final, irreversible decision for the year 2050.

### 3. Results

#### 3.1. Impact of time inconsistency on energy planning

This section presents the primary results derived from the above-described setup. These findings aim to highlight the impact of decision makers' short-term bias and temporally-inconsistent preferences on the trajectory of the power system toward decarbonization. These findings are, however, conditional on the assumptions made in this paper about the specification of discount rate curves, each reflecting a distinct attitude of decision makers toward time. In reality, different attitudes toward time, more or less prone to inconsistency, may arise. The focus of the analysis is on key indicators for the power sector, including the cost-optimal power mix, CO<sub>2</sub> emissions from power generation, and system costs. Results from the time-consistent simulations are primarily used for diagnostic purposes and for determining the available CO<sub>2</sub> budget for the examined time horizon. Results are reported until 2050, the final year for which planning decisions are revised.

The first-order effect of introducing time inconsistency into the model is a change in the cost-effective portfolio of power technologies over the remaining modeling horizon, which spans from the updated planning year to the end of the horizon (both of which advance by one year at each step). This occurs because future years are evaluated from an increasingly advanced point in time: the implied short-term-biased social planner assigns greater importance to the same future years than in the previous step, while also considering one additional year beyond the previously evaluated horizon. Consequently, successive plan revisions lead to different investment decisions and utilization patterns across power technologies, which in turn affect the pace of decarbonization and system costs. Moreover, the policy mechanisms considered to achieve decarbonization introduce varying degrees of flexibility in the

extent to which time-consistent decisions can be overturned, potentially leading to sub-optimal pathways that may be difficult to reverse.

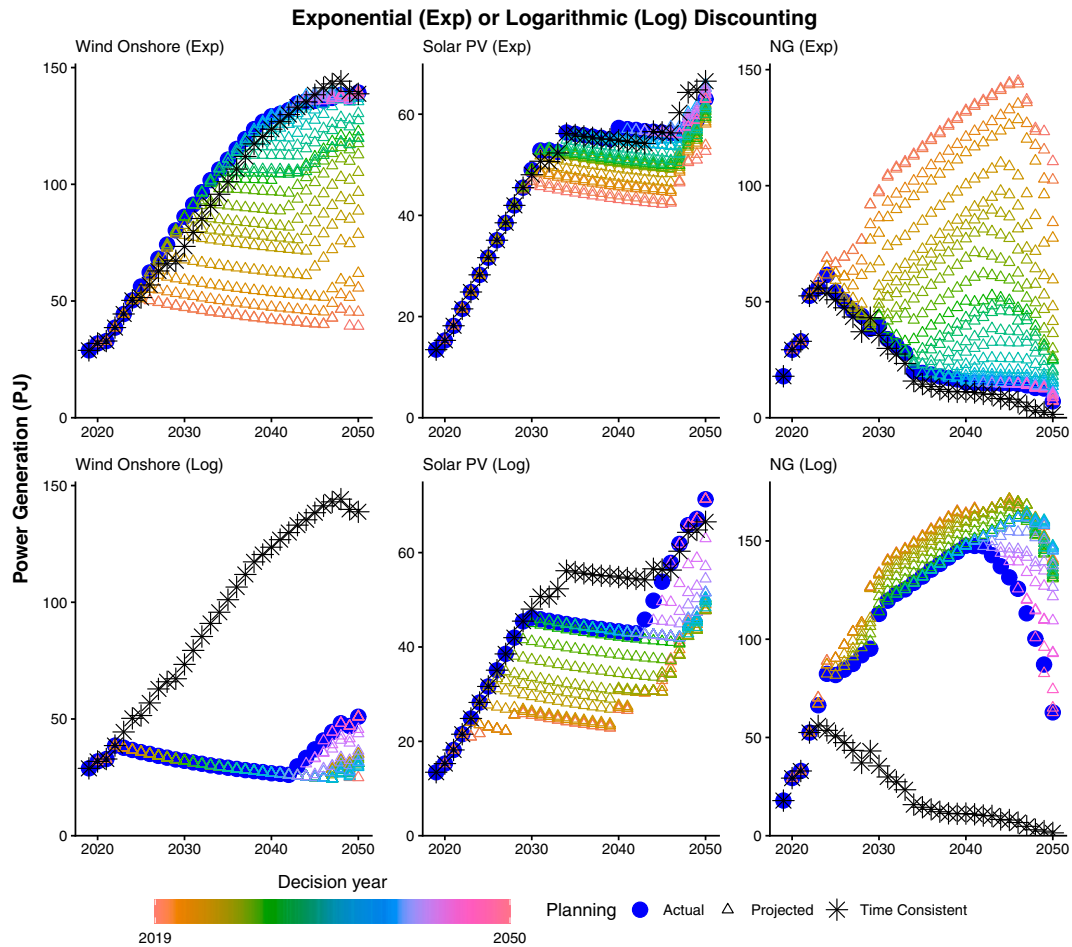
This variability in energy planning decisions is shown in Figs. 3 and 4, which reflect the scale of the impact of time inconsistency in each case. Specifically, these figures depict the annual power generation over 2019–2050 for the key technologies exhibiting both high variability under time inconsistency and a substantial share in the power mix, namely wind onshore, solar PV, and natural gas (NG). Fig. 3 corresponds to the scenarios involving carbon prices (CPS), while Fig. 4 represents the scenarios entailing an emission budget (CBS). Triangles represent decisions made for future years at earlier planning stages (i.e., more than one year ago), with the color reflecting the respective planning year. Blue circles indicate decisions made for the same year, which are final and irreversible ("actual" decisions), while black asterisks denote the decisions from the time-consistent simulation (i.e., perfect foresight with a fixed discount rate). The outcomes for the remaining technologies, which either exhibit minimal variation across planning years or insignificant contributions, are illustrated in Figs. A.1–A.4 in Appendix A. It should be noted that, in some cases, invariability against time inconsistency is exogenously imposed through hard constraints on technology deployment in the model, as for example happens for the phase out of coal power technologies (refer to Section 2.2 for further details).

In all cases, the primary driver of variability in technology utilization across different planning years is the interplay between natural gas infrastructure and renewable technologies. When decision makers attribute more importance to the short term, it becomes economically rational to delay system decarbonization — i.e., continue using the incumbent fossil fuel technologies (natural gas in this case, as the phase out of the other fossil fuel technologies is imposed exogenously) and postpone further investments in renewable technologies. However, as their effective planning horizon extends (i.e., as they place greater weight on longer-term outcomes), they can see the economic consequences of their previous choices (i.e., increased carbon price costs or capital investment requirements to comply with the carbon budget). Consequently, they revise previous plans, shifting toward renewable technologies.

Scenarios with carbon pricing (Fig. 3) demonstrate this more clearly, due to the higher flexibility they allow in terms of reaching specific mitigation goals. Specifically, early plans with exponential discount rate involve up to 10 times more natural gas generation in 2050 than what is finally deployed then. Similarly, wind generation is increased many-fold to cover much of the gap, with smaller increases seen for solar PV. Although carbon pricing scenarios under logarithmic discounting follow similar trends, they exhibit much smaller discrepancies between planned and final, actual outcomes: natural gas retains a more significant role still in 2050, while wind deployment is ignored for most of the time frame and cannot be scaled up as quickly as would be cost effective by the end of the time horizon.

On the other hand, the differences between planned and final deployments are smaller under carbon budget scenarios (Fig. 4), although the same general pattern emerges: natural gas use is traded off against renewable technologies, but now in terms of the timing of the transition. The emission budget-driven trajectories may be interpreted as embodying a reduced transformation risk, as the shared view of the implied decision makers across the modeling horizon about the need to meet the budgets leads to more gradual and consistent development of the technologies. This reduced risk stems from the increased resilience against potential system disruptions (e.g., grid bottlenecks), negative economy-wide repercussions (e.g., those arising from elevated capital investment requirements for rapid installation of power technologies; [10,33]) and feasibility constraints.

To sum up, the results on technology deployment reflect how decision makers with a short-term focus prioritize natural gas, as it entails lower short-term costs, postponing the renewable investments until later. The periodic revision of the plans over time, however, slowly pivots them away from natural gas, at least to the extent that they still have the possibility to do so. Such strategic shifts result in



**Fig. 3.** Annual power generation in PJ of the critical technologies exhibiting high variability against time inconsistency and a high share in the power mix, for the scenarios involving a carbon price (CPS). The results are visualized across different planning years, marked with distinct colors. Final, irreversible decisions made for the given year are marked with blue circles. Triangles depict decisions from the forward-looking planning (i.e., more than one year ahead), with colors indicating the corresponding planning year. Black asterisks indicate the trajectory from the time-consistent simulation. Each sub-figure title consists of the technology name followed by the type of discount rate curve used across different planning years in parentheses (“Exp” for exponential and “Log” for logarithmic).

significant variations in technology deployment for the same future years, especially in the absence of a carbon budget to limit the flexibility.

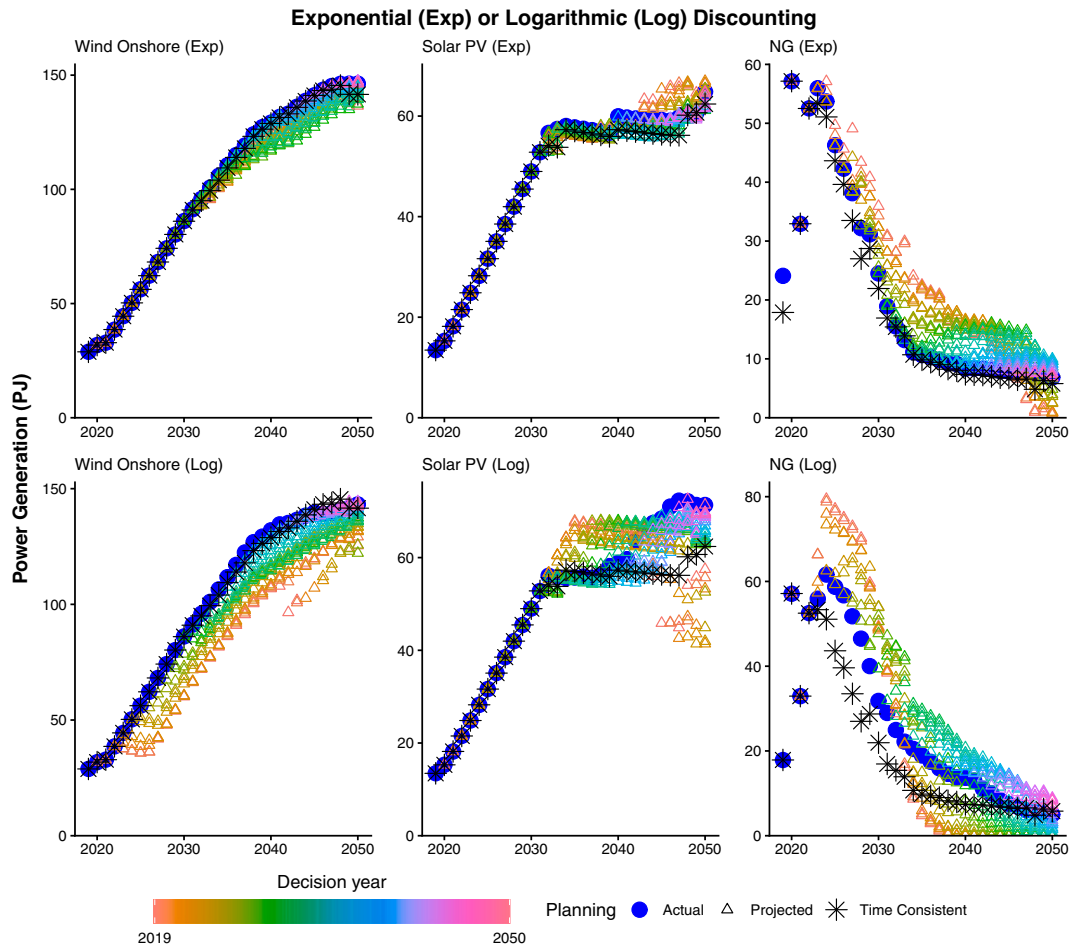
As expected, this variability in technology usage across planning years and policy scenarios also translates into variability in the emissions from power generation, as depicted in Fig. 5. This figure depicts the annual CO<sub>2</sub> emissions in megatons from power generation over 2019–2050 across the various temporally-inconsistent scenarios. The marking of results from different planning years and from the time-consistent simulation follows the same convention as in the power mix results (see above for details). The first row displays temporally inconsistent scenarios based on carbon pricing, while the second row corresponds to those based on a carbon budget. The left-hand figures assume exponentially-increasing discount rates, whereas the right-hand figures apply logarithmically-increasing discount rates.

As shown in Fig. 5, regarding the time-consistent simulations, as the emissions need to be brought down significantly and there are limits to how quickly this can be done (and the social planner sees the full horizon with a steady attitude toward time preference), in broad terms the results look similar across the two policy mechanisms, carbon prices and budgets. Specifically, the scenario with carbon prices is, due to the high carbon price for 2050, able to reach the decarbonization goal in 2050, whereas with a carbon budget residual emissions still remain — and more is done before 2030 to stay under the emission budget. It is worth noting that the increase in emissions in 2023

across the scenarios is attributed to the commissioning of the lignite power “Ptolemaida V”, which we include in our modeling. However, across the time-inconsistent simulations, the two policy implementation mechanisms, CPS and CBS, differ fundamentally in the flexibility they allow for emission levels, and this is clearly reflected in the variability of emission results.

The runs in which a budget constraint is applied can only reallocate mitigation across time, but cannot alter the total emission budget. This results in a fairly small divergence of the time-inconsistent plans from both the actual, yearly planning and the time-consistent pathway (see the bottom panels in Fig. 5). Although of small scale, the logarithmic discount rate leads to a higher divergence than the exponential rate, with which the early plans suggest near zero emissions already for the mid 2030s, to allow higher emissions for the later periods. With carbon prices, we can observe a different story. The model reacts to the price level, the costs of which are discounted, leading to a wide range of plans for any given year and, with logarithmic discounting, to a trajectory of final decisions that diverges strongly from the corresponding time-consistent scenario.

Interestingly, the different policy mechanisms also lead to different directional corrections to plans, once the decision year is moved forward. With CPS policies the carbon tax payments from future years initially matter less, as they are discounted with a high discount rate, but become more meaningful the closer the decision making point is to the



**Fig. 4.** Annual power generation in PJ of the critical technologies showing high variability under time inconsistency and a large share in the power mix, for the scenarios involving an emission budget (CBS). Different colors denote the variability of results across different planning years. Final, irreversible decisions made for the given year are marked with blue circles. Triangles depict forward-looking decisions (i.e., more than one year ahead), with colors indicating the corresponding planning year. Black asterisks indicate the pathway from the time-consistent simulation. Each sub-figure title is composed of the technology name and the type of discount rate curve used across different planning years in parentheses (“Exp” for exponential and “Log” for logarithmic).

planning year. As a consequence, early planning suggests much higher emission levels, which are then brought down in the plans that follow. Conversely, with the budget constraint and high discount rates, it’s sensible to postpone as much as possible of the mitigation until later. Over time, the costs related to reaching near-zero emission levels already in the 2030s become more meaningful, and plans are revised to mitigate more early on and allow emissions to remain above zero for longer — in fact, throughout the whole time horizon.

What’s also interesting is that for the carbon price case the need for revising investment decisions in the future is more pronounced with exponential discount rates (done through a quicker phase out of NG-fueled technologies), whereas for the carbon budget the logarithmic discount rates lead to larger differences between the initial and final decisions. If compared to the outcomes of the time-consistent simulation, however, the logarithmic discount rate case diverges more strongly than the exponential one does — and in CPS the difference is significant. As the final decisions are always made with the same discount rate, this illustrates how the different valuations of the future have pushed decisions in this scenario to a path from which there is no fast return. Of the two discount rate formulations, this one has a clearer “right now” bias and the results illustrate the potentially destructive impacts of it.

The sub-optimal development trajectory resulting from short-term bias and temporal inconsistencies increases system costs. However, revising planning decisions can significantly reduce these costs and bring

them closer to those of the time-consistent simulation, as depicted in Fig. 6. This figure illustrates how the net present value (NPV) of cumulative system costs over the 2019–2070 period decreases under each step of planning revision process, while costs incurred prior to the revision year remain unchanged. Planning revisions occur sequentially; for example revising planning in 2030 implies that planning has also been revised in all preceding years shown on the x-axis. Therefore, the reduction in total system costs observed in each case reflects the cumulative effect of all previous planning revisions. These costs include both the capital investment requirements and operating (fixed and variable) costs. In the carbon pricing scenarios, system costs additionally include carbon costs, computed as the product of annual power sector’s emissions with the corresponding carbon prices.

The effect of planning revisions is especially pronounced in terms of cost reductions for the carbon-pricing scenarios and under exponential discounting (this reflects the greater reversibility of early planning decisions toward the time-consistent trajectory compared with the logarithmic discounting case). However, after 2030, the cost reductions from further revisions are only minimal in this scenario, as the decision maker stops being myopic and sees the full time horizon from that point (albeit still with a short-term bias). Conversely, under logarithmic discounting, system costs don’t come so close to those of the time-consistent scenario, as the system has locked into a trajectory that is difficult to reverse. This is because this scenario involves a more aggressive devaluation of the

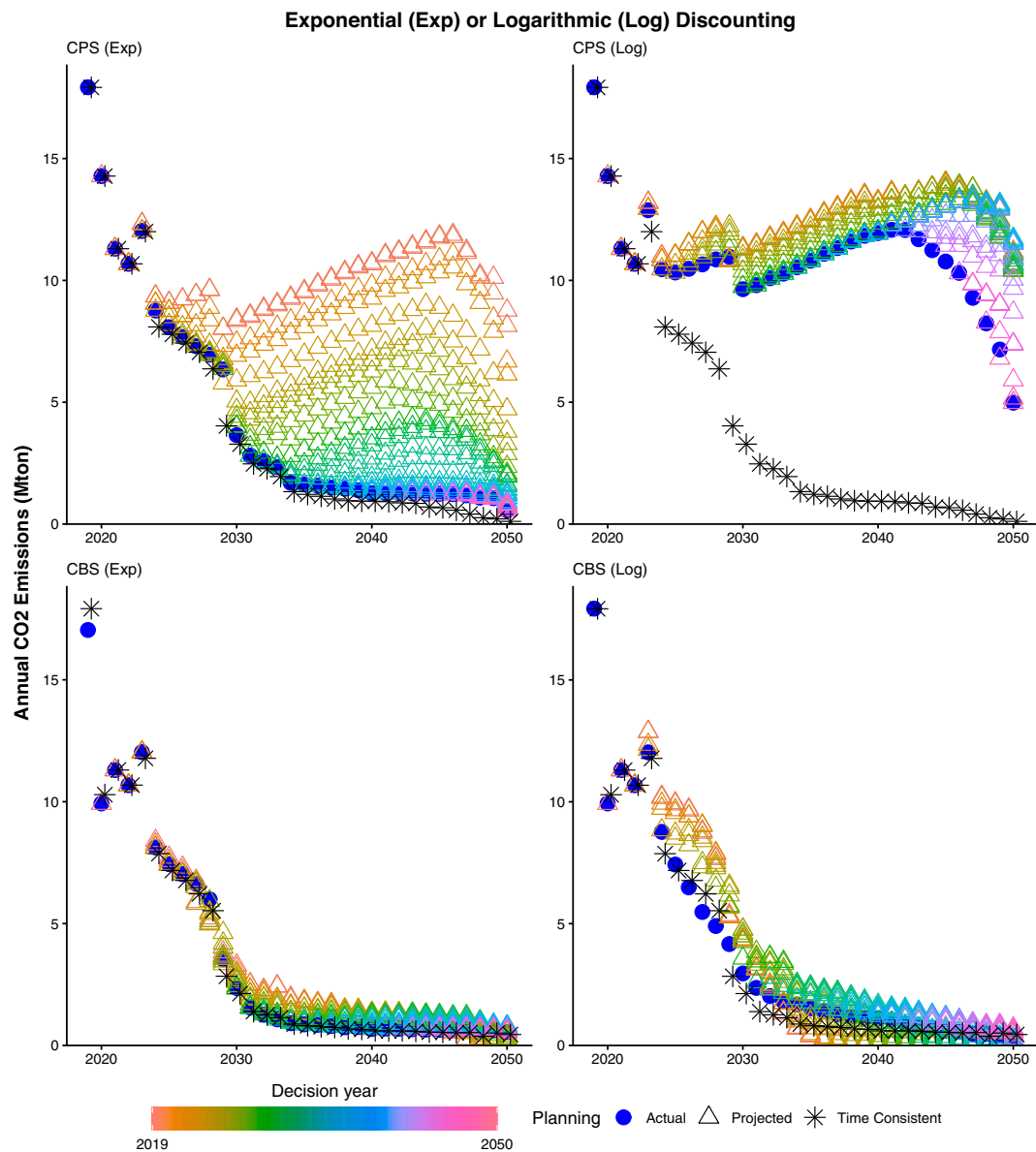


Fig. 5. Annual emissions in Megatons of CO<sub>2</sub> from power generation over the 2019–2050 period. Emissions from forward looking plans are marked with triangles, with different colors representing different planning years. Emissions from the final, irreversible decisions made for the given year are marked with blue circles, while black asterisks denote the trajectory of the time-consistent scenario. Each sub-figure title specifies the policy mechanism applied under each scenario, carbon pricing (CPS) or an emission budget (CBS), and the type of discount-rate curve used across planning years in parentheses (“Exp” for exponential and “Log” for logarithmic).

future and a soft policy constraint. This continued operation of the system away from the cost-optimal pathway results in significantly higher costs compared to the time-consistent simulation.

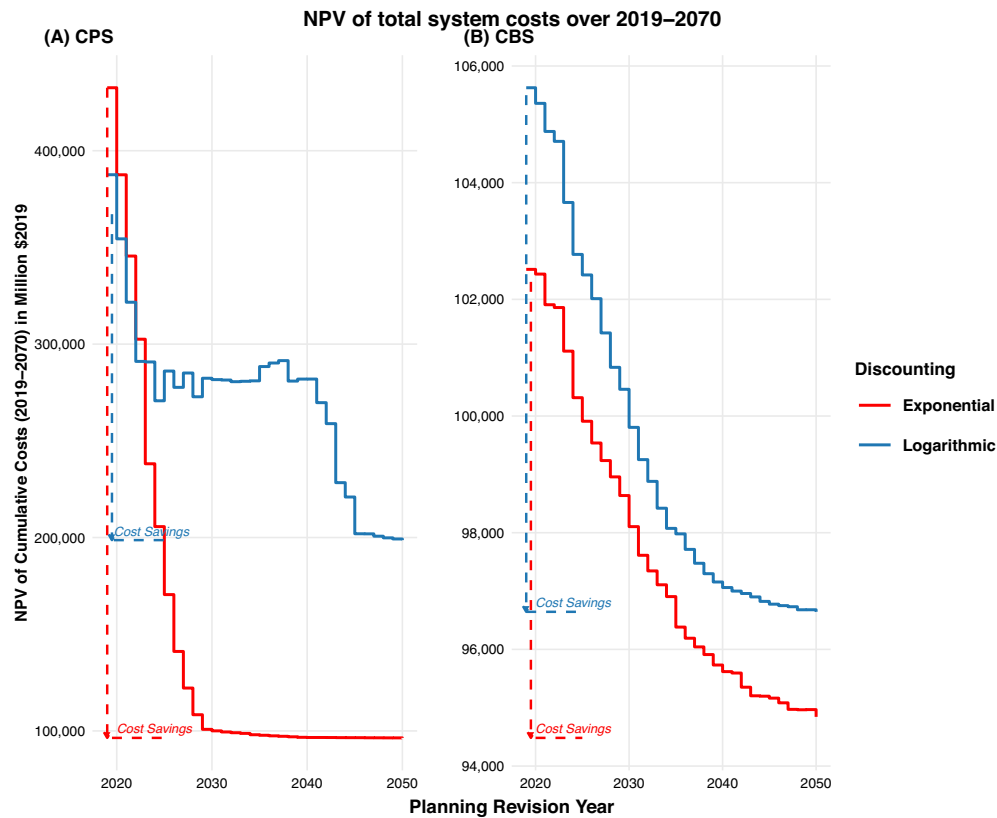
This path irreversibility results also in a non-monotonic relationship between planning revisions and system costs: there are a few cases when planning revision leads to slightly higher system costs (see Panel A Fig. 6). However, overall and especially toward the end of the horizon, planning revisions generally lead to significant cost reductions. Consequently, short-term bias can result in profoundly increased costs when there’s the flexibility for postponing decarbonization for later. These impacts, however, are mitigated in scenarios encompassing an emission budget, where the higher interconnectedness of decisions over time lessens this effect. In this case, costs come much closer to the time-consistent pathway and continue to decrease in a consistent fashion throughout the whole period (high pathway irreversibility).

However, cost savings from planning revisions are smaller in relative terms compared to the CPS scenarios.

The general trend revealed by this figure is that early planning with a short-term bias passes transformation costs onto later periods and therefore to future generations, increasing inter-generational injustices. Revising plans results in attributing more importance to the future, thereby assigning higher costs to nearer-term periods. This, in turn, brings the system’s trajectory closer to the time-consistent scenario, especially under the emission budget case.

### 3.2. Robustness check of results under real-world energy planning constraints

In this section, we evaluate the relevance of our time-inconsistency framework in a real-world energy planning context. In practice, there



**Fig. 6.** Net present value (NPV) of cumulative system costs in million US\$2019 (including capital investments, operational expenses, and carbon costs) over 2019–2070 under annual rolling planning revisions. Step-wise lines reflect the change in total system costs from the base year’s perspective (i.e., 2019) when planning is revised annually, while previously incurred costs are kept fixed. Panel (A) presents results for the CPS scenarios and Panel (B) for the CBS scenarios, each categorized by the form in which future is depreciated in each case, either exponential or logarithmic.

is a lead time between planning decisions and infrastructure realization, for example, due to construction times and regulatory processes. Consequently, energy planning decisions exhibit inertia and may not be easily overturned after a certain point.

Although we introduce our time-inconsistency framework in a generic form with an arbitrary time step  $n$ , we adopt a one-year step in our application to study the effects of time inconsistency with a high level of temporal granularity. To analyze the impact of our current step length and lack of explicit lead time, we examine how planning decisions for a given milestone year evolve during the five years preceding that milestone. Specifically, we compute for selected milestone years capacity additions (in GW) as determined by planning decisions made within the last five years before the milestone year, i.e., planning for each milestone is first formulated five years in advance and then revised annually until the milestone year is reached. We visualize the results in Fig. 7, which reflects the sensitivity of investment decisions to annual planning updates under a five-year lead time, thereby allowing us to assess whether revisions overturn decisions that, in reality, would likely already be committed.

As shown in the figure, the planning for the milestone year does change during the preceding five years, but generally not through canceling previously planned projects, but by adding new ones. This is because the planner sees in each revision that increasing mitigation stringency in the milestone year is now economically viable, thereby deciding to add more renewable technology capacity. The added capacities are largely not investments that require extensive lead times (e.g., nuclear or natural gas), but instead mainly pertain to solar and wind

energy, which tend to have much shorter planning cycles. There are, however, also in some cases new investments in biomass and geothermal technologies that might struggle to materialize by the milestone year, if explicit lead times were included.

We thus conclude that increasing the time step beyond one year or introducing explicit lead times for technologies would likely have only a marginal impact on the results for this specific application. However, in other cases, the relevance of results to real-world conditions should be examined, and explicit constraints may be introduced to limit the extent to which energy investment decisions can be revised. It’s also worth noting that, although construction times aren’t modeled explicitly, they are reflected in the overnight capital investment costs included in the model.

#### 4. Discussion and conclusions

Despite providing critical insights into the cost-optimal trajectory of the energy system to meet projected demands and environmental goals, time-consistent ESOMs fail to capture various elements that affect the actual trajectory of the energy system. Key elements include decision makers’ short-term biases, temporally-inconsistent preferences, and dynamic decision making in response to new information. This study advances the existing body of literature by exploring the impact of such factors within an optimization model encompassing a high level of technological detail. This approach recognizes that real-world decision makers are aware of, and therefore don’t completely disregard, future targets as fully myopic models do, but that they are incentivized to push

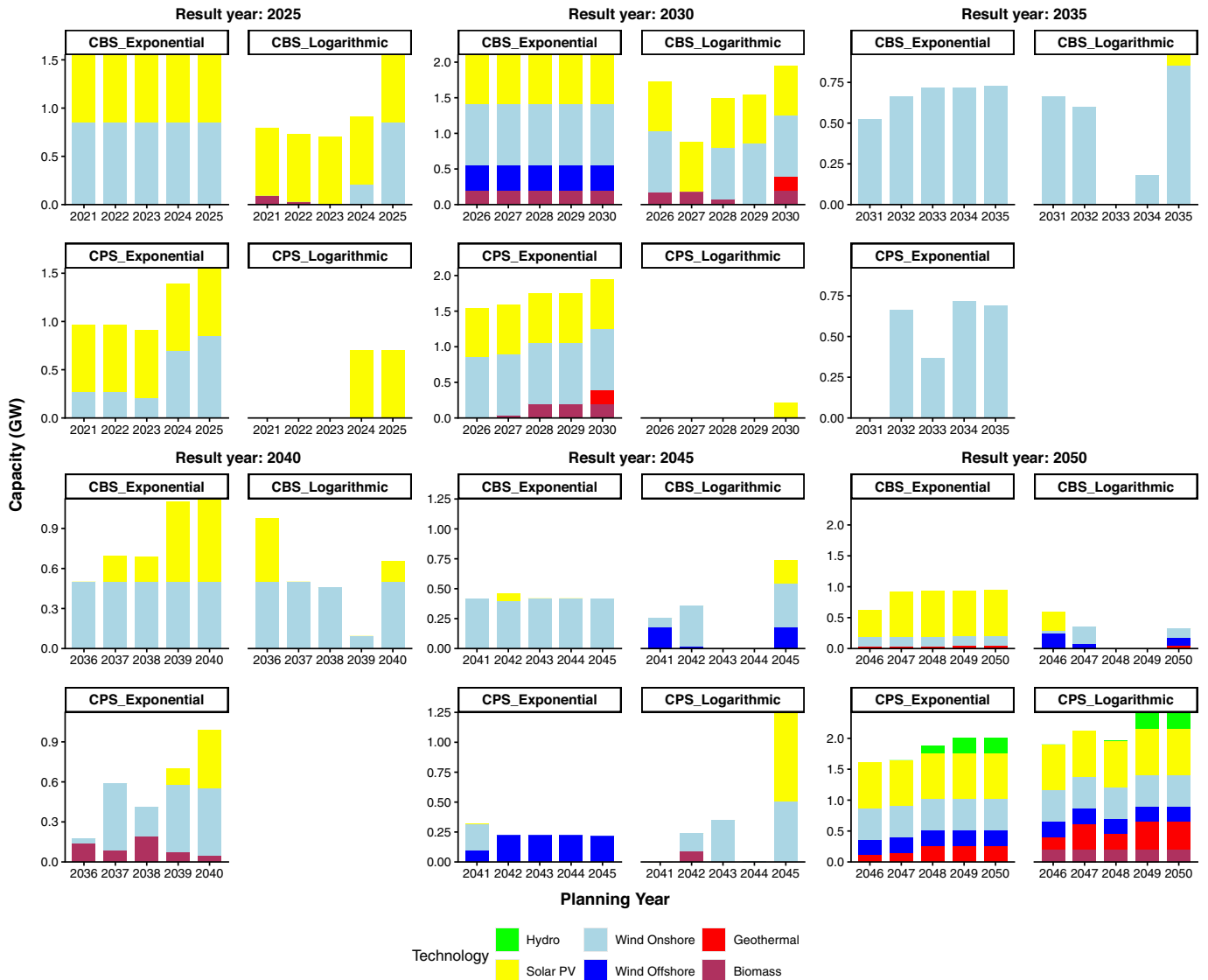


Fig. 7. Investment decisions in the form of capacity additions (in GW) for selected milestone years (i.e., 2025, 2030, 2035, 2040, 2045, and 2050), based on planning decisions made during the five years preceding each milestone. The scope of this figure is to illustrate the sensitivity of investment decisions to the updates in the planning year for a five-year lead time. Each panel is labeled according to the policy mechanism used for decarbonization—carbon prices (CPS) or carbon budget (CBS)—followed by the type of discounting applied, either exponential or logarithmic. When a panel is blank, it indicates that there are no new capacity additions for that milestone year in the examined scenario.

the costs of the transition to the future, incurring higher costs over the full transition period.

This is achieved by introducing a modeling framework that involves a sequential decision-making approach, where decisions are annually revised based on the previous year’s results and the decision makers’ updated valuation of the future. The analysis applies this framework to explore decarbonization scenarios for Greece’s power sector over the 2019–2050 period, each involving mechanisms with varying levels of path dependency and commitment. These scenarios are simulated with a cost-optimization model that accounts for the temporal inconsistencies of decision makers through increasing discount rate curves, while time-consistent scenarios are also considered for diagnostic purposes. The analysis focuses on the implications of temporal inconsistencies on system configuration and the ensuing costs and emissions.

The outcomes of the analysis underscore that temporal inconsistency materially alters the system configuration: when the future is valued differently or viewed through different temporal lenses, the “optimal”

course of action changes as well. Furthermore, it is not only the presence of short-term preferences that matters, but also their intensity. That said, stronger short-term biases can lead to significantly different pathways compared to weaker short-term biases. These pathways may involve unbalanced long-term plans that cannot return to consistent trajectories, even with later planning revisions. Furthermore, by increasing mitigation costs and pushing them to the future, these time-related biases can increase inter-generational injustices. Additionally, delaying decarbonization due to short-term interests leads to a more rapid system transformation in later periods, thereby heightening transition risks and endangering the whole transition overall. Acknowledging that today’s decisions are often made with limited foresight, skewed perspectives, and a bias toward immediate concerns, emphasizes the importance of regular revision of energy system strategies adopted. The periodic revision of the original plans can assist in alleviating the impacts of these biases, thereby preventing commitments to sub-optimal pathways and better balancing short-term actions with long-term objectives.

Nonetheless, in some cases, this may still be not enough, as strong short-term biases may lead to irreversible pathways.

The analysis has some important practical policy and research implications. From a policy perspective, the findings highlight that strengthening coordination across successive energy planning decision makers is critical. When such coordination exists, the central policy question concerns the appropriate pace of decarbonization. When it does not, the more fundamental issue becomes the shape of the transition, which may be irreversible: there is the risk of locking into sub-optimal pathways in which the energy system cannot decarbonize in a timely manner. Moreover, specifying both the speed and the endpoint of the transition—such as through a binding net-zero target—is essential to prevent rebound effects or policy reversals.

Regular revision of energy strategies can partially mitigate short-term bias by incorporating updated information and reducing long-term lock-in. This sequential decision making becomes effective when guided by a strict long-term target (e.g., carbon budget); such policy targets, if considered binding by current and future decision makers alike, can create strong interdependencies across planning years and leave less flexibility to delay system transformation. However, in the absence of path dependency in energy planning decision making, strong short-term biases can have irreversible effects even with planning revision. Beyond policy measures that establish path dependency (e.g., legally binding carbon budgets), placing expert committees independent of political influence in charge of making energy planning decisions or establishing certain checks and balances can ensure a consistent energy transition.

Regarding the implications for energy system modeling community, when the goal is to advise on, and gain insights into, the optimal trajectory of the system, time-consistent, perfect-foresight simulations should be chosen. Such scenarios showcase economically optimal and consistent investment decisions. However, these insights are conditional on the assumptions made in the analysis about the future socio-economic and technological evolution, thereby making it essential to account for the diversity of possible futures and how these may affect results. Conversely, when the goal is to simulate what is likely to happen on the ground, incorporating the behavioral attributes of decision making into energy system models is fundamental for generating robust insights. However, even in this case, informing decision makers with the results of cost-optimal economic models can help them improve their decisions, particularly when short-term biases operate subconsciously. However, such guidance may be less effective when short-term biases are driven by conscious objectives, such as political considerations.

The implications for the research community extend also to the aspect of reversibility: when evaluating the robustness or preferability of energy strategies, it is important to consider pathway reversibility (e.g., flexibility of commitments, diversity of technology options) as a criterion, since new information may emerge over time. Such information may be expected from energy planners (“known unknowns”; e.g., updated fuel prices) or may be unexpected (“unknown unknowns”; e.g., new evidence on technology impacts; [32]). Consequently, beyond economic efficiency, environmental soundness, fairness, and other typical objectives, an energy pathway should also possess the flexibility to adjust to a new “optimal direction” in response to such information in the medium or long term. Notably, “unknown unknowns”—which are inherent in energy strategies that extend many decades into the future—may require more abrupt adjustments to energy pathways (e.g., many mitigation options adopted today were debated or viewed differently decades ago).

It is important to note that our modeling framework remains agnostic regarding the drivers behind decision makers’ short-term bias and temporal inconsistency—i.e., no differentiation between preference-driven

short-term bias and rational responses to uncertainty. Since the implied social planner has perfect foresight at each step, the model does not explicitly represent rational responses to uncertainty (e.g., policy and technology risks or strategic wait-and-see behavior) nor real-world myopia. Instead, these effects are indirectly reflected through the exogenous updating of the base year and the discount rate curves, which alter the effective decision horizon and intertemporal preferences. For example, a year occurring 30 years after the base year always receives the same weight; however, the corresponding calendar year shifts as planning is revised. By updating the effective decision horizon at each step, social planners are called upon to update their decisions in light of new circumstances for the same future years.

Future research could extend this framework by endogenizing the drivers of short-term bias, for example, by incorporating stochastic decision-making approaches instead of recurring deterministic optimization with perfect foresight (e.g., stochastic programming or robust optimization). Such approaches could more realistically represent the myopia faced by real-world decision makers. In contrast to conventional myopia studies that impose a rolling planning window by truncating the terminal year, or to our framework (which is not fully myopic, as decision makers can still foresee infeasibilities and react to them), rational decision makers typically account for anticipated future changes in socio-economic conditions when making decisions, although they do not have perfect foresight about their exact realization. This could be modeled, for instance, by allowing decision makers to face multiple possible realizations of input data, each associated with a specific probability of occurrence, instead of a single deterministic dataset assumed under a perfect foresight setting. They could then optimize their decisions according to different decision-making principles—for example, selecting pathways that avoid worst-case outcomes, minimize regrets, or perform well on average. Subsequently, decisions could be updated as new information becomes available and probabilities of future outcomes are revised.

Future research could also explore the inter-sectoral and inter-regional impacts of time inconsistency on power sector planning; for example, how delayed investments in the power sector can affect the trajectory of the transport sector, or how short-term bias in the decision making of developed countries could influence the decarbonization efforts of developing nations. Additionally, linking a macroeconomic model with an optimization model would allow the quantification of the feedback on the wider economy from time-inconsistent decisions in the energy system. Furthermore, the proposed temporal inconsistency framework could be applied in a global model driven solely by a climate damage function (e.g., Nordhaus [27]), to simulate flexible budget scenarios, in which climate impacts relate to the size of the budget. Under such scenarios, high future damages would concern policymakers only a little when they are far away, but would be impossible to reverse when they are close to hitting them.

#### CRediT authorship contribution statement

**Diamantis Koutsandreas:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ilkka Keppo:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

#### 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.

Appendix A. Power generation of non-critical technologies

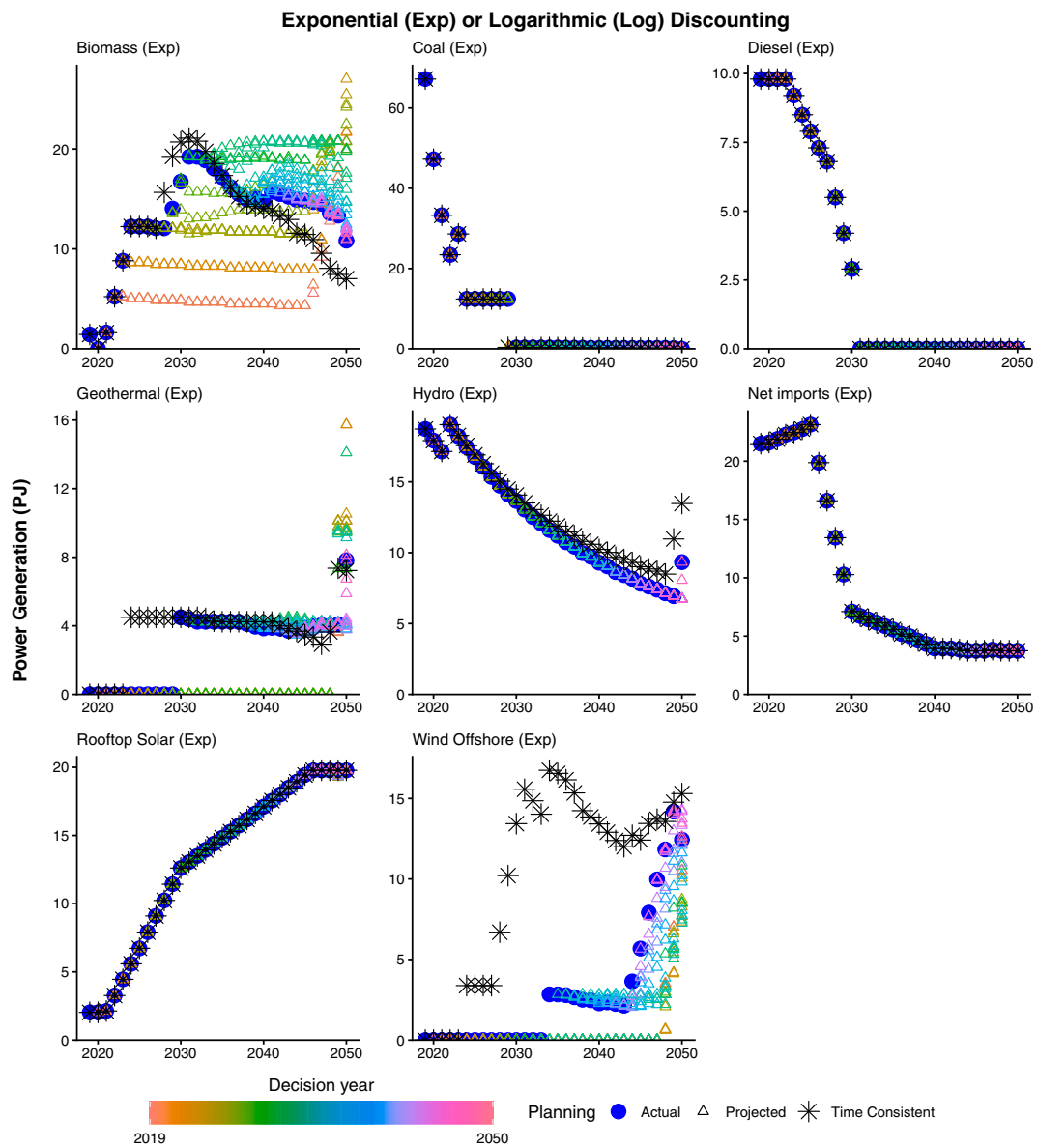
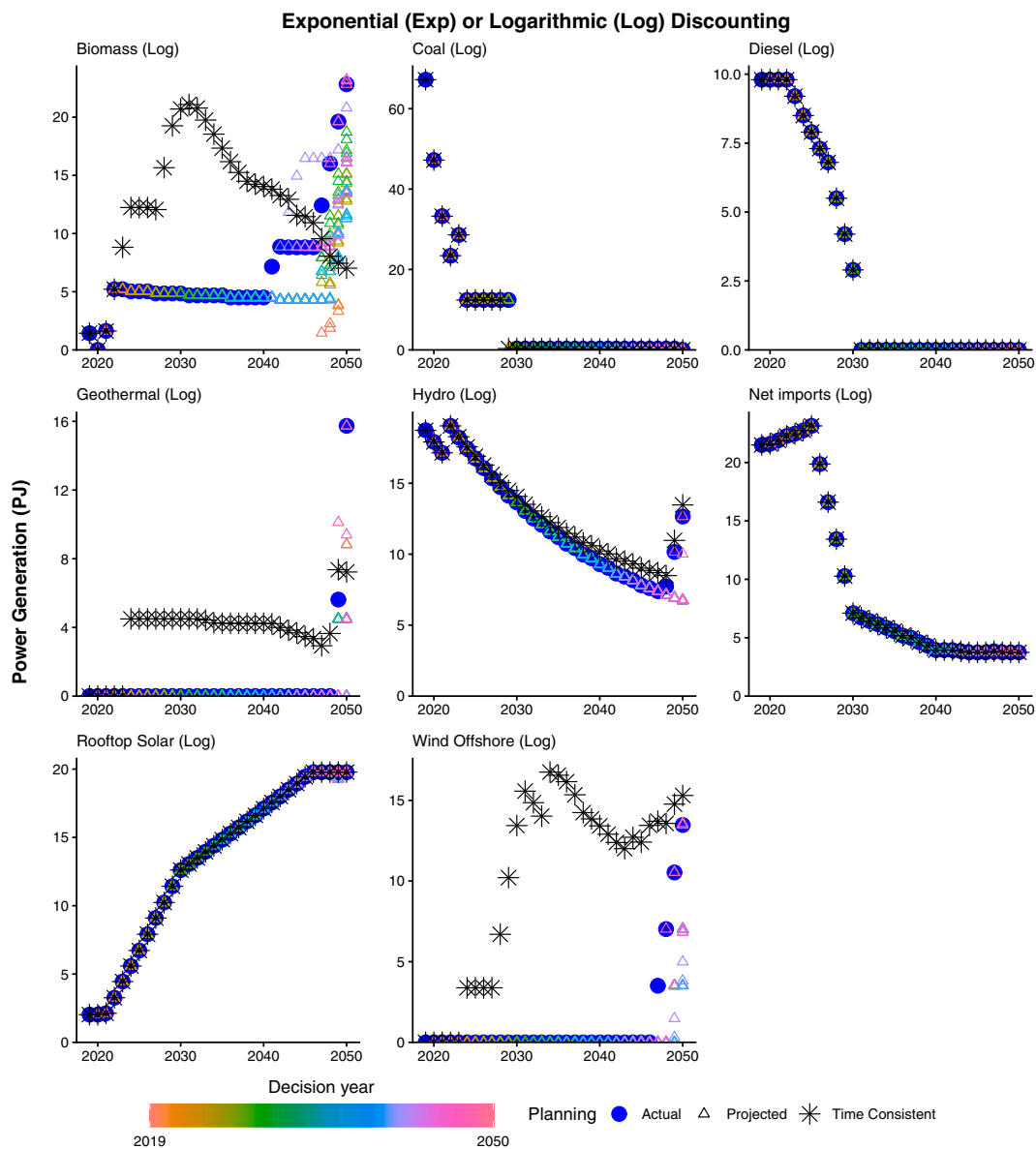
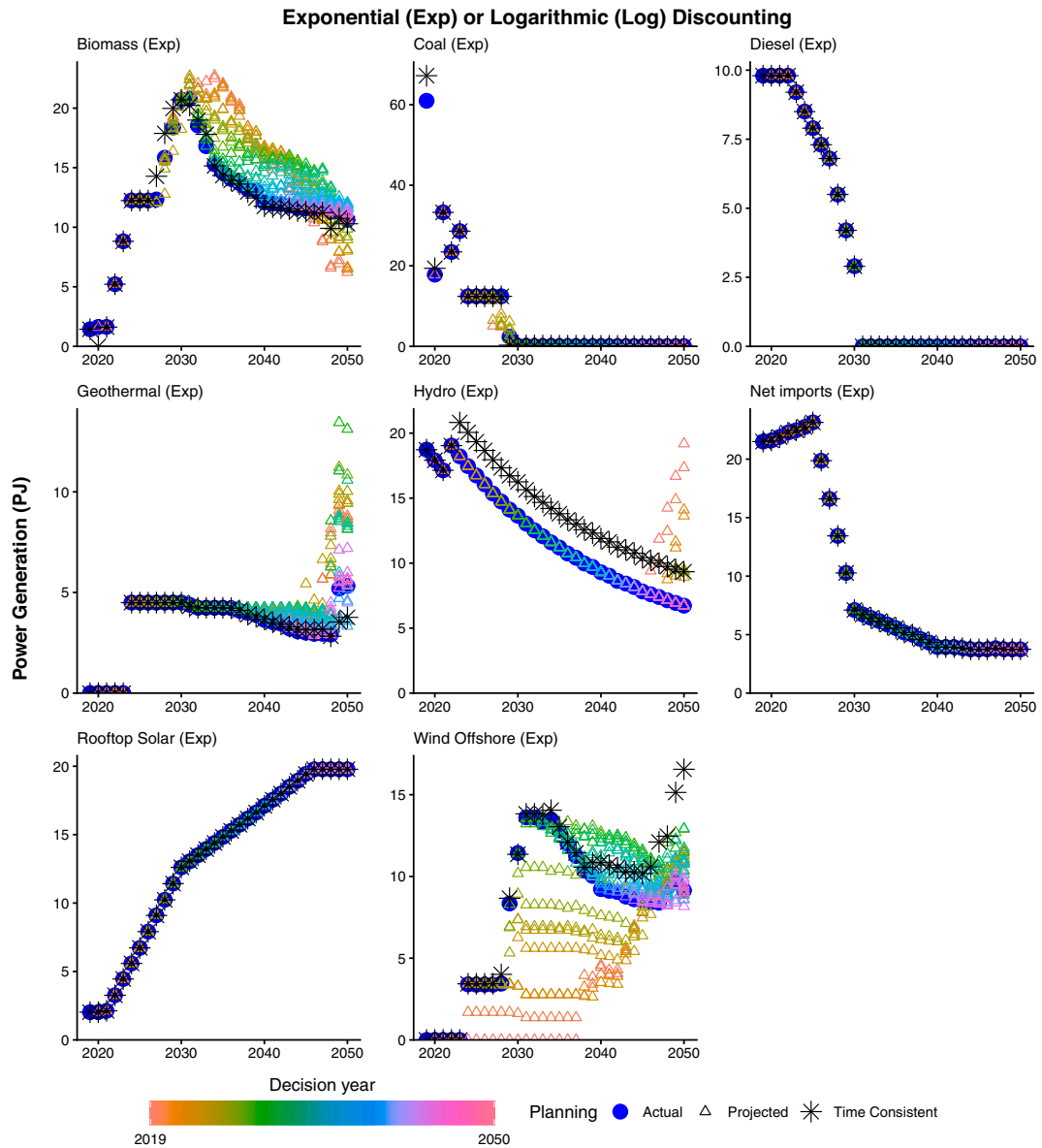


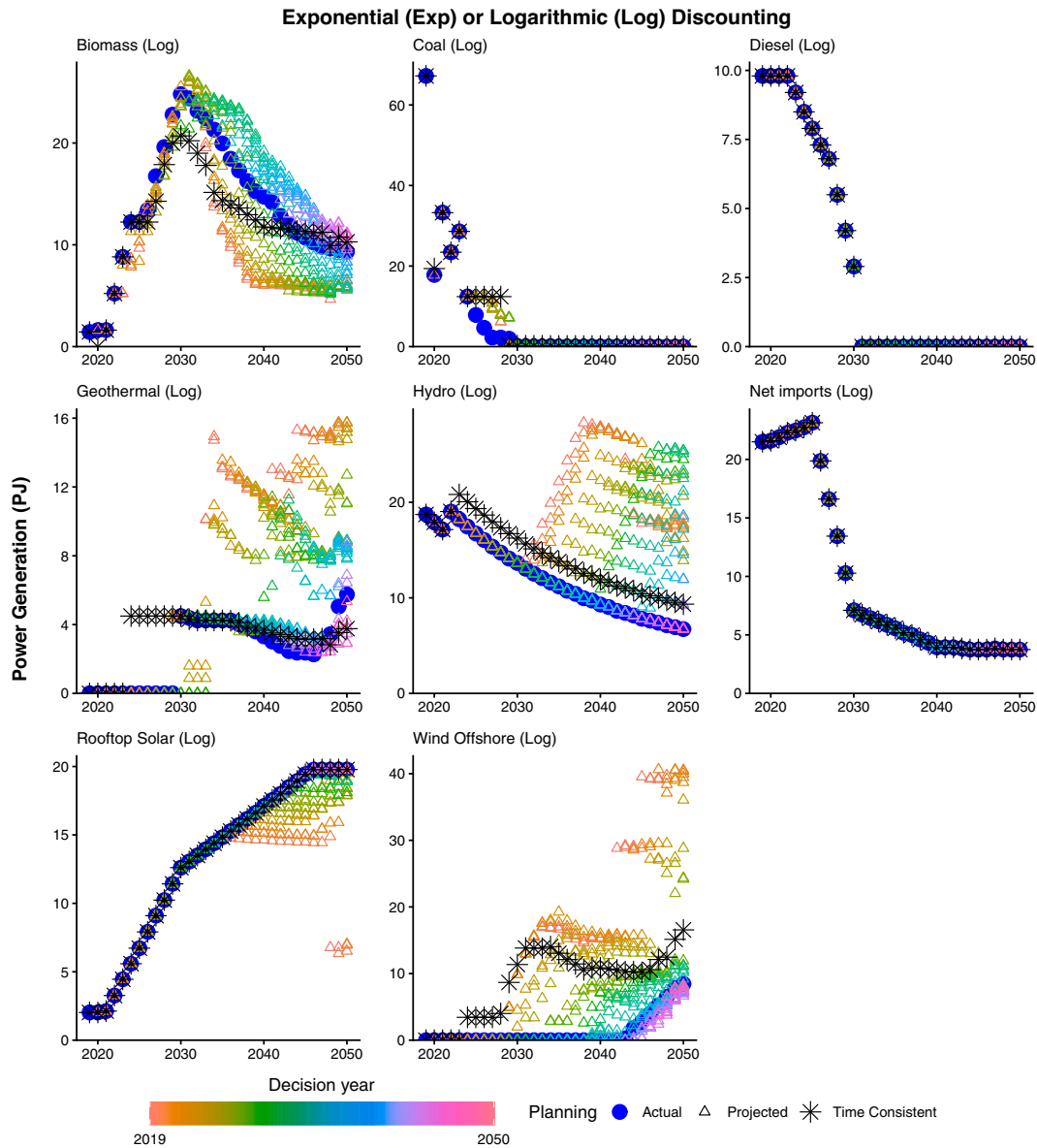
Fig. A.1. Annual production of the non-critical power technologies for the Greek power sector across different planning years in the scenarios involving carbon prices and exponentially increasing discount rates. Results from the first year (actual planning) are marked with blue circles, versus triangles depicting the projected planning. Black asterisks indicate the trajectory from the time-consistent simulation.



**Fig. A.2.** Annual production of the non-critical power technologies for the Greek power sector across different planning years for the scenarios involving carbon prices and logarithmically increasing discount rates. Results from the first year (actual planning) are marked with blue circles, with triangles depicting the projected planning. Black asterisks depict the trajectory from the time-consistent simulation.



**Fig. A.3.** Annual production of the non-critical power technologies for the Greek power sector across different planning years for the scenarios involving an emission budget and exponentially increasing discount rates. Results are visualized across different planning years, marked with distinct colors. Results from the first year (actual planning) are marked with blue circles, versus triangles depicting the projected planning. Black asterisks indicate the trajectory from the time-consistent simulation.



**Fig. A.4.** Annual production of the non-critical power technologies for the Greek power sector across different planning years for the scenarios involving an emission budget and logarithmically increasing discount rates. Results are visualized across different planning years, marked with distinct colors. Results from the first year (actual planning) are marked with blue circles, versus triangles depicting the projected planning. Black asterisks indicate the trajectory from the time-consistent simulation.

**Data availability**

Data will be made available on request.

**References**

[1] Augenblick N, Niederle M, Sprenger C. Working over time: dynamic inconsistency in real effort tasks. *Q J Econ* 2015;130:1067–115.

[2] Van der Brugge R, Rotmans J, Loorbach D. The transition in Dutch water management. *Reg Environ Change* 2005;5:164–76.

[3] Chiappinelli O, May N. Too good to be true? Time-inconsistent renewable energy policies. *Energy Econ* 2022;112:106102. <https://doi.org/10.1016/j.eneco.2022.106102>. <https://www.sciencedirect.com/science/article/pii/S0140988322002614>.

[4] Constantino SM, Sparkman G, Kraft-Todd GT, Bicchieri C, Centola D, Shell-Duncan B, Vogt S, Weber EU. Scaling up change: a critical review and practical guide to harnessing social norms for climate action. *Psychol Sci Public Interest* 2022;23:50–97.

[5] DeCarolis J, Daly H, Dodds P, Keppo I, Li F, McDowall W, Pye S, Strachan N, Trutnevte E, Usher W, Winning M, Yeh S, Zeyringer M. Formalizing best practice for energy system optimization modelling. *Appl Energy* 2017;194:184–98. <https://doi.org/10.1016/j.apenergy.2017.03.001>. <https://www.sciencedirect.com/science/article/pii/S0306261917302192>.

[6] European Commission. Guide to cost-benefit analysis of investment projects. 2014. [https://wayback.archive-it.org/12090/20221203224508/https://ec.europa.eu/inea/sites/default/files/cba\\_guide\\_cohesion\\_policy.pdf](https://wayback.archive-it.org/12090/20221203224508/https://ec.europa.eu/inea/sites/default/files/cba_guide_cohesion_policy.pdf) [Accessed: 27 October 2023].

[7] Frederick S, Loewenstein G, O'Donoghue T. Time discounting and time preference: a critical review. *J Econ Lit* 2002;40:351–401. <https://doi.org/10.1257/002205102320161311>. <https://www.aeaweb.org/articles?id=10.1257/002205102320161311>.

[8] Freeman M, Groom B, Spackman M. Social discount rates for cost-benefit analysis: a report for HM treasury. London, UK: HM Treasury; 2018. [https://assets.publishing.service.gov.uk/media/6983375013622473b51ca9ca/Social\\_Discount\\_Rates\\_for\\_Cost-Benefit\\_Analysis\\_A\\_Report\\_for\\_HM\\_Treasury.pdf](https://assets.publishing.service.gov.uk/media/6983375013622473b51ca9ca/Social_Discount_Rates_for_Cost-Benefit_Analysis_A_Report_for_HM_Treasury.pdf).

[9] Fuso Nerini F, Keppo I, Strachan N. Myopic decision making in energy system decarbonisation pathways. A UK case study. *Energy Strate Rev* 2017;17:19–26. <https://doi.org/10.1016/j.esr.2017.06.001>. <https://www.sciencedirect.com/science/article/pii/S2211467X17300287>.

[10] Gambhir A, George M, McJeon H, Arnell NW, Bernie D, Mittal S, Köberle AC, Lowe J, Rogelj J, Monteith S. Near-term transition and longer-term physical climate risks of greenhouse gas emissions pathways. *Nat Clim Change* 2022;12:88–96.

- [11] García-Gusano D, Espegren K, Lind A, Kirkengen M. The role of the discount rates in energy systems optimisation models. *Renew Sustain Energy Rev* 2016;59:56–72. <https://doi.org/10.1016/j.rser.2015.12.359>. <https://www.sciencedirect.com/science/article/pii/S1364032116000253>.
- [12] Haasnoot M, Kwakkel JH, Walker WE, ter Maat J. Dynamic adaptive policy pathways: a method for crafting robust decisions for a deeply uncertain world. *Glob Environ Change* 2013;23:485–98. <https://doi.org/10.1016/j.gloenvcha.2012.12.006>. <https://www.sciencedirect.com/science/article/pii/S095937801200146X>.
- [13] Hallegatte S, Shah A, Brown C, Lempert R, Gill S. Investment decision making under deep uncertainty—application to climate change. *World Bank Policy Res Work Pap* 2012;6193.
- [14] Hansson SO, Lillqvist K, Björnberg KE, Johansson MV. Time horizons and discount rates in Swedish environmental policy: who decides and on what grounds? *Futures* 2016;76:55–66. <https://doi.org/10.1016/j.futures.2015.02.007>. <https://www.sciencedirect.com/science/article/pii/S0016328715000300>. policy-making for the long term: puzzling and powering to navigate wicked futures issues.
- [15] Heinzl C, Winkler R. Distorted time preferences and time-to-build in the transition to a low-carbon energy industry. *Environ Resour Econ* 2011;49:217–41.
- [16] HMEE. National energy and climate plan; hellenic ministry of environment and energy. 2019. [https://commission.europa.eu/publications/greece-draft-updated-necp-2021-2030\\_en](https://commission.europa.eu/publications/greece-draft-updated-necp-2021-2030_en) [Accessed: 30 August 2024].
- [17] Keppo I, Butnar I, Bauer N, Caspani M, Edelenbosch O, Emmerling J, Fragkos P, Guivarch C, Harmsen M, Lefevre J, et al. Exploring the possibility space: taking stock of the diverse capabilities and gaps in integrated assessment models. *Environ Res Lett* 2021;16:053006.
- [18] Keppo I, Strubegger M. Short term decisions for long term problems – the effect of foresight on model based energy systems analysis. *Energy* 2010;35:2033–42. <https://doi.org/10.1016/j.energy.2010.01.019>. <https://www.sciencedirect.com/science/article/pii/S0360544210000216>.
- [19] Kivimaa P, Heikkinen M, Huttunen S, Jaakkola JJK, Juhola S, Juntunen S, Kaljonen M, Käyhkö J, Leino M, Loivaranta T, et al. Evaluation of justice in climate policy. 2023. Technical Report. Suomen ilmastopaneeli.
- [20] Koutsandreas D. A nexus-based impact assessment of rapid transitions of the power sector: the case of Greece. *Electricity* 2023;4:256–76. <https://doi.org/10.3390/electricity4030016>. <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85172105740&doi=10.3390>.
- [21] Koutsandreas D, Keppo I. On the macroeconomic and societal ramifications of green hydrogen policies — the case of Greek transport sector. *Energy* 2025;315:134389. <https://doi.org/10.1016/j.energy.2025.134389>. <https://www.sciencedirect.com/science/article/pii/S0360544225000313>.
- [22] Koutsandreas D, Trachanas GP, Pappis I, Nikas A, Doukas H, Psarras J. A multicriteria modeling approach for evaluating power generation scenarios under uncertainty: the case of green hydrogen in Greece. *Energy Strateg* 2023;50:101233. <https://doi.org/10.1016/j.esr.2023.101233>. <https://www.sciencedirect.com/science/article/pii/S2211467X23001839>.
- [23] Koutsandreas D, Zamanipour B, Keppo I. A multicriteria modelling framework for evaluating clean energy transitions: the case of Greece as electricity exporter. *Renew Energy* 2026;256:124622. <https://doi.org/10.1016/j.renene.2025.124622>. <https://www.sciencedirect.com/science/article/pii/S0960148125022864>.
- [24] Martinsen D, Krey V, Markewitz P. Implications of high energy prices for energy system and emissions—the response from an energy model for Germany. *Energy Policy* 2007;35:4504–15. <https://doi.org/10.1016/j.enpol.2007.03.003>. <https://www.sciencedirect.com/science/article/pii/S0301421507000936>.
- [25] Martinsen D, Krey V, Markewitz P, Vogele STEFAN. A time step energy process model for Germany—model structure and results. *Energy Stud Rev* 2006;14:35.
- [26] Mertens J-F, Rubinchik A. Intergenerational equity and the discount rate for policy analysis. *Macroecon Dyn* 2012;16:61–93. <https://doi.org/10.1017/S1365100510000386>.
- [27] Nordhaus WD. *Managing the global commons: the economics of climate change*, vol. 31. MIT Press Cambridge, MA; 1994.
- [28] Nordhaus WD. A review of the stern review on the economics of climate change. *J Econ Lit* 2007;45:686–702.
- [29] Ranger N, Millner A, Lopez A, Ruta G, Hardiman A. Adaptation in the UK: a decision making process: technical annexes. *Retr Jan* 2010;29:2013.
- [30] Silvi M, Padilla Rosa E. A tragedy of the horizons? An intertemporal perspective on public support for carbon taxes. *Energy Econ* 2023;125:106815. <https://doi.org/10.1016/j.eneco.2023.106815>. <https://www.sciencedirect.com/science/article/pii/S0140988323003134>.
- [31] Steinbach J, Staniaszek D. Discount rates in energy system analysis: discussion paper. 2015. [https://www.bpie.eu/wp-content/uploads/2015/10/Discount\\_rates\\_in\\_energy\\_system-discussion\\_paper\\_2015\\_ISI\\_BPIE.pdf](https://www.bpie.eu/wp-content/uploads/2015/10/Discount_rates_in_energy_system-discussion_paper_2015_ISI_BPIE.pdf).
- [32] Stirling A. Keep it complex. *Nature* 2010;468:1029–31. <https://doi.org/10.1038/4681029a>.
- [33] Sun J, Yang Y, Zhou P. Low-carbon transition risks in the energy sector: a systematic review. *Sustain Prod Consum* 2024;50:115–27. <https://doi.org/10.1016/j.spc.2024.07.025>. <https://www.sciencedirect.com/science/article/pii/S235255092400215X>.
- [34] Trutnevte E. Does cost optimization approximate the real-world energy transition? *Energy* 2016;106:182–93. <https://doi.org/10.1016/j.energy.2016.03.038>. <https://www.sciencedirect.com/science/article/pii/S0360544216302821>.
- [35] Usher W, Barnes T, Moksnes N, Niet T. Global sensitivity analysis to enhance the transparency and rigour of energy system optimisation modelling. *Open Res Eur* 2023;3:30.
- [36] Zhuang J, Liang Z, Lin T, De Guzman F. Theory and practice in the choice of social discount rate for cost-benefit analysis: a survey. 2007. Technical Report. ERD working paper series.