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Consequences of the missing risk market problem for power system emissions

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ABSTRACT

Liberalized power markets are characterized by a missing market problem: a limited availability of long-term contracts leaves risk-averse investors exposed to uninsured risk. We explore how this problem affects a power system's capacity mix and overall emissions. For this purpose, we develop a new equilibrium generation expansion model that endogenously captures investors' risk exposure in incomplete markets. Our approach addresses the problem of multiple equilibria and, partly, the computational burden inherent to such models. We solve our model for an abstract system with gas, wind, solar, and battery storage under demand and gas price uncertainty. The results first show that, when risk markets are missing, investment risk can cause higher emissions and less clean energy investment than what would be implied by a model that omits investment risk. The impact of risk on investment depends only partly on technologies' capital intensities and largely on how technologies interact at the systems level. We also compare system outcomes with missing long-term markets to the socially optimal case, where risk-averse investors and consumers trade risk via complete long-term markets. In the absence of long-term markets, we observe higher emissions, less investment in renewables and storage, and more investment in gas. These results suggest that long-term market mechanisms for electricity generation and storage may advance climate goals while addressing inefficiencies in current markets.

1. Introduction

Investments in electricity technologies face irreducible uncertainty which exposes investors to financial risk. Risk is a central concern for investors because they are generally believed to be risk-averse. The degree of risk investors are exposed to strongly depends on their ability to hedge risk via long-term markets.[1] Markets generally fail to provide for optimal risk hedging (Radner, 1970; Stiglitz, 1982; Staum, 2007), which is also known as the missing market problem (Newbery, 2016; Keppler et al., 2022). Research has shown that this market failure can significantly affect power system resource adequacy (Abada et al., 2019; Mays et al., 2022; Billimoria et al., 2022). Here, we investigate the implications of the missing market problem for power system emissions.

Multiple sources of uncertainty bear on electricity investments. Increasingly relevant is uncertainty in long-term electricity demand, which has become less predictable due to uncertain new demand from electrification, hydrogen electrolysis, and direct air capture (Larson et al., 2020). Fuel prices are another important source of uncertainty. The volatility of gas prices increased in the early 21st century relative to the preceding three decades (Sherwin et al., 2018). It then played a central role in the global energy crisis of the early 2020s. Policy changes and other uncertainties, including in interannual meteorology, may also affect investments. This paper focuses on demand and gas price uncertainty.

How uncertainty impacts power system investments has been extensively studied using stochastic optimization (Roald et al., 2023). However, past research often omitted the role of risk by assuming investors to be risk-neutral (Hu and Hobbs, 2010; Leibowicz, 2018; Scott et al., 2021). Here, drawing on finance theory, we assume investors to be risk-averse, and proceed to characterize their risk exposure.

Investors manage risk by trading financial contracts that hedge the risk from a given investment. Markets are commonly assumed to be complete: i.e., to feature financial instruments that span all risks, so that investors can insure themselves against any possible realization of the future (Munoz et al., 2017; Diaz et al., 2019; Möbius et al., 2023). However, it is well established that real markets fall short of this ideal

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[1] The terms "long-term markets" and "risk markets" are used interchangeably in this paper.

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Nomenclature

Indices and Sets

$s \in S$	Demand scenarios
$f \in F$	Fuel cost scenarios
$t \in T$	Time steps (hours)
$r \in R$	Technology resources
$G \subset R$	Generation technologies (gas, wind, solar)
$O \subset R\ (O \cap G = \emptyset)$	Storage technologies (batteries)
$\alpha, \alpha^{inv}, \alpha^{iso}$	Sets containing the variables of the central planner, investors, and the system operator

Parameters

D_{ts}	Demand (MWh)
C^{var}_{rf}	Variable cost ($/MWh)
C^{inv}_{r}	Investment cost ($/MW)
C^{cap}	Price cap ($/MWh)
P_{sf}	Probability of demand s and gas price f (fraction)
Ω	Weight for risk aversion (fraction)
Ψ	Probability level used to parameterize risk aversion (fraction)
A_{rt}	Availability of generation resource (fraction)
F^{ch}	Charging efficiency (fraction)
F^{dch}	Discharging efficiency (fraction)
N^{s}_{r}	Power to energy ratio for storage technologies (fraction)
W_t	Weight of representative period (fraction)
E^{co2}_{r}	Emissions intensity (tCO_2/MWh)

Variables

g_{rtsf}	Generation (MWh)
x_r	Capacity (MW)
y_{tsf}	Load shedding (MWh)
e_{rtsf}	Energy stored, i.e., state of charge (MWh)
z^{ch}_{rtsf}	Charging of storage technology (MWh)
z^{dch}_{rtsf}	Discharging from storage technology (MWh)
ζ^{cp}	Value-at-Risk (VaR) for central planner ($)
u^{cp}_{sf}	Additional cost relative to VaR for central planner ($)
ζ_r	VaR for investor in technology r ($)
u_{rsf}	Loss relative to VaR for investor in technology r ($)
$\tilde{\zeta}$	VaR for investor in all technologies ($)
$\tilde{u}_{sf}$	Loss relative to VaR for investor in all technologies ($)
π_{rsf}	Revenues net of operating costs ($/MW)

Dual variables

λ_{tsf}	Price of electricity ($/MWh)
μ_{rtsf}	Generation capacity rent ($/MW)
$\phi^{soc}_{rtsf}, \phi^{cap}_{rtsf}, \phi^{c}_{rtsf}, \phi^{d}_{rtsf}, \phi^{bal}_{rtsf}, \xi^{d}_{rtsf}$	Dual variables corresponding to storage constraints
θ_{rsf}	Risk-adjusted probability (fraction)
$\tilde{\theta}_{sf}$	Risk-adjusted probability for investor in all technologies (fraction)

(Radner, 1970; Stiglitz, 1982; Staum, 2007). In power systems, an important hedging strategy is the use of long-term forward contracts between investors and consumers, an example being the use of Power Purchase Agreements (PPAs). PPAs can replace a variable stream of revenues with a more stable return based on a pre-negotiated price and sometimes volume. However, consumers have generally shown low willingness to sign long-term PPAs (de Maere d'Aertrycke et al., 2017; Neuhoff et al., 2022; Keppler et al., 2022; Wolak, 2022; Batlle et al., 2023). Power systems are thus characterized by a missing market problem (Newbery, 2016). As a result, investors are exposed to more risk than is socially optimal, which makes missing markets a problem for policy makers as well as investors (Keppler et al., 2022). This paper explores the implications of the missing market problem for climate goals in particular.

We focus on two main questions. First, we assess how accounting for investors' risk exposure in an absence of risk markets changes modeled investments and emissions compared to what would be implied by the more common risk-neutral modeling approach. This comparison allows us to isolate the effects of investment risk on the power system. Second, we consider how an absence of risk markets between risk-averse investors and consumers impacts investments and emissions relative to an optimal system where risk-averse investors and consumers trade risk via complete risk markets.

Previous work addressing our second question suggested that market incompleteness could hinder decarbonization because clean energy technologies are relatively capital intensive (Neuhoff and De Vries, 2004). However, technologies differ not only in capital intensity but also in the degree of risk they face. Mays and Jenkins (2023) modeled different technologies' risk exposures in incomplete markets and showed that gas plants can face more risk than renewables. These results demonstrate the importance of modeling risk within a systems framework that endogenously captures each technology's unique risk exposure. A growing literature addresses this need by employing equilibrium methods for generation expansion, which often model risk aversion using the Conditional Value-at-Risk (CVaR) function. Some studies in this literature partly addressed our first question (Ehrenmann and Smeers, 2011; Meunier, 2013; Bichuch et al., 2023) and others partly our second question (de Maere d'Aertrycke et al., 2017), but these studies did not model variable renewables or storage. Recent work included renewable generation but omitted renewable investments (Hoschle et al., 2018; Billimoria et al., 2022), or did not analyze how investment varies with risk exposure (Pineda et al., 2018). Mays et al. (2019) modeled wind investment and found it decreases with incomplete markets relative to complete markets, but did not model storage or show how risk impacts investment relative to the more traditional risk-neutral modeling approach. Mays and Jenkins (2023) modeled wind, solar, and 1-h battery investments to assess the degree of risk in a power system with a high penetration of renewables but did not isolate the effect of market incompleteness on the technology mix or on carbon emissions. Here, we extend this literature by investigating how market incompleteness impacts the capacity mix and emissions of a power system featuring variable renewables and storage.

Modeling risk-averse generation expansion with missing risk markets presents challenges due to the non-convex nature of the equilibrium problem (Ehrenmann and Smeers, 2011). The associated computational burden makes it difficult to capture the inter-temporal behavior of a system with variable renewables and storage. Additionally, solutions are subject to the possibility of multiple equilibria (Gérard et al., 2018). Previous work has addressed the former problem with specialized algorithms (Hoschle et al., 2018; Mays et al., 2019). Here, we demonstrate a non-algorithmic method, which enables us to address the latter challenge and partly the former for an abstract power system featuring both variable renewables and storage.

This paper's first contribution is a new approach to modeling risk-averse generation expansion with missing markets. We build on the common equilibrium-based approach with CVaR (Ehrenmann and

Smeers, 2011) but introduce a reformulation which provides computational advantages that allow us to model both variable renewables and storage. Our method includes an exact linear reformulation of a non-convex term commonly present in equilibrium risk-averse models. We also demonstrate how the storage investment problem can be formulated in an equilibrium framework. Another advantage of our approach is that it allows us to introduce a numerical robustness procedure, analogous to modeling to generate alternatives (DeCarolis, 2011), to systematically test for multiple equilibria.

This work's second contribution is an analysis of how the missing market problem impacts emissions, as well as how it impacts investments in variable renewables and storage. We investigate the mechanisms behind the impact of risk on the capacity mix, and distinguish between the impacts of each technology's unique risk premium, its capital intensity, and its system value. We thus extend prior work which emphasized the role of capital intensity (Neuhoff and De Vries, 2004; Tietjen et al., 2016). Our systems perspective also complements the large technology-level literature on the role of risk in clean energy investments (Polzin et al., 2019; Dukan and Kitzing, 2023, e.g.).

The results first show that the risks investors face in the absence of risk markets can lead to less clean energy investment and higher emissions compared to what would be indicated by traditional risk-neutral modeling. Second, in exploratory experiments comparing a power system with missing markets to an optimal system with complete markets, we observe higher emissions and a shift in investment from renewables and storage toward fossil fuel plants when risk markets are missing. This suggests that an absence of long-term markets may distort power system outcomes in a way that interferes with climate policy goals.

2. Methods

2.1. Introduction to the analytical framework for risk-averse generation expansion with missing markets

Exposure to risk equates to an additional cost of capital (Markowitz, 1952), known as the risk premium, which effectively increases a project's investment cost. We model the risk investors are exposed to in an absence of risk markets by following a common approach in the generation expansion literature (Ehrenmann and Smeers, 2011; Hoschle et al., 2018; de Maere d'Aertrycke et al., 2017; Mays et al., 2019). The way in which this method captures the effect of risk on investment decisions has been well described before (de Maere d'Aertrycke et al., 2017; Mays et al., 2022). Here, we provide a brief introduction.

The modeling framework represents generation expansion as a two-stage stochastic optimization problem. In the first stage, risk-averse investment decisions are made, and, in the second stage, market clearing occurs for every scenario.[2] The revenues investors earn in each scenario depend on the market-clearing outcome of that scenario as well as any risk trading. An absence of risk markets is modeled by disaggregating the generation expansion problem into separate optimization problems belonging to different market agents. The effect of this disaggregation is to relax the assumption of complete risk trading implicit in the traditional optimization-based central planner framework (Munoz et al., 2017). We distinguish between investors and a system operator agent that represents the consumer side of the market, in the mold of prior work (Ehrenmann and Smeers, 2011). Our focus is on the missing risk trading between investors and consumers, which drives our main results. Our main formulation defines a separate investor agent for each technology, but we also show the implications of allowing for a "representative investor" to invest in all technologies (Section 2.3.2).

[2] Uncertainty is represented by a discrete probability distribution.

Risk aversion is modeled using CVaR, which causes decision makers to weight downside scenarios[3] more heavily (where the weight is exogenously determined). This has the effect of increasing the expected revenues that are required to trigger investment compared to the expected revenues in a risk-neutral case. In this way, the model captures how risk exposure increases an investment's required rate of return, which corresponds to an increase in the cost of capital. The model thus endogenizes the cost of capital. In Section 3.1, we derive each technology's Weighted Average Cost of Capital (WACC) from the model, and show how it impacts technologies' costs.

2.2. Optimization model of generation expansion (complete risk markets)

We first formulate a classical generation expansion optimization problem with the addition of risk aversion. The solution of the model can be interpreted as the optimal planning decisions of a risk-averse central planner, or as the equilibrium outcome in a perfectly competitive market with complete risk trading between risk-averse investors and risk-averse consumers (Munoz et al., 2017). For tractability, our modeling throughout this paper only considers perfectly competitive, energy-only markets and omits unit commitment and grid constraints.

The optimization model takes the form of a linear, two-stage stochastic program including risk aversion. The representation of risk aversion follows the standard approach by Rockafellar and Uryasev (2002) using the CVaR measure. Uncertainty is represented by allowing for stochasticity in demand, represented by indexing the inelastic demand parameter D_{ts} by scenarios $s \in S$, and stochasticity in fuel cost, captured by indexing the variable cost parameter C^{var}_{rf} by scenarios $f \in F$.

$$\begin{aligned} \min_{\alpha} \quad & \sum_r C^{inv}_r x_r \\ & + \Omega\left[\sum_s \sum_f P_{sf} \sum_t W_t \sum_r C^{var}_{rf} g_{rtsf} \right. \\ & \left. + \sum_s \sum_f P_{sf} \sum_t W_t C^{cap} y_{tsf} \right] \\ & + (1-\Omega)\left[\zeta^{cp} + \frac{1}{\Psi} \sum_s \sum_f P_{sf} u^{cp}_{sf} \right] \end{aligned} \tag{1a}$$

$$\text{s.t.} \quad x_r \geq 0 \quad \forall\, r \in R \tag{1b}$$

$$g_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{1c}$$

$$e_{rtsf}, z^{ch}_{rtsf}, z^{dch}_{rtsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{1d}$$

$$y_{tsf} \geq 0 \quad \forall\, t \in T, s \in S \tag{1e}$$

$$u^{cp}_{sf} \geq 0 \quad \forall\, s \in S, f \in F \tag{1f}$$

$$\zeta^{cp} \in \mathbb{R} \tag{1g}$$

$$u^{cp}_{sf} \geq \sum_t W_t \sum_r g_{rtsf} C^{var}_{rf} + \sum_t W_t C^{cap} y_{tsf} - \zeta^{cp} \quad \forall\, s \in S, f \in F \; (\tilde{\theta}_{sf}) \tag{1h}$$

$$\sum_r^{|G|} g_{rtsf} + \sum_r^{|O|} \left[z^{dch}_{rtsf} - z^{ch}_{rtsf} \right] + y_{tsf} = D_{ts} \quad \forall\, t \in T, s \in S, f \in F \; (\lambda_{tsf}) \tag{1i}$$

$$g_{rtsf} \leq x_r A_{rt} \quad \forall\, r \in G, t \in T, s \in S, f \in F \; (\mu_{rtsf}) \tag{1j}$$

$$e_{r1sf} = e_{r|T|sf} - \frac{1}{F^{dch}} z^{dch}_{r1sf} + F^{ch} z^{ch}_{r1sf} \quad \forall\, r \in O, s \in S, f \in F \; (\phi^{soc}_{r1sf}) \tag{1k}$$

$$e_{rtsf} = e_{rt-1sf} - \frac{1}{F^{dch}} z^{dch}_{rtsf} + F^{ch} z^{ch}_{rtsf}$$

[3] The model endogenously determines which scenarios represent downside risk for each technology.

$$\forall\ r \in O, t \in \{2, 3, \dots, |T|\}, s \in S, f \in F\ (\phi^{soc}_{rtsf}) \tag{1l}$$

$$e_{rtsf} \le \frac{1}{N^s_r} x_r \quad \forall\ r \in O, t \in T, s \in S, f \in F\ (\phi^{cap}_{rtsf}) \tag{1m}$$

$$z^{ch}_{rtsf} \le x_r \quad \forall\ r \in O, t \in T, s \in S, f \in F\ (\phi^{c}_{rtsf}) \tag{1n}$$

$$z^{dch}_{rtsf} \le x_r \quad \forall\ r \in O, t \in T, s \in S, f \in F\ (\phi^{d}_{rtsf}) \tag{1o}$$

$$z^{dch}_{r1sf} \le e_{r|T|sf} \quad \forall\ r \in O, s \in S, f \in F\ (\xi^{d}_{r1sf}) \tag{1p}$$

$$z^{dch}_{rtsf} \le e_{rt-1sf} \quad \forall\ r \in O, t \in \{2, 3, \dots, |T|\}, s \in S, \\ f \in F\ (\xi^{d}_{rtsf}) \tag{1q}$$

$$z^{dch}_{rtsf} + z^{ch}_{rtsf} \le x_r \quad \forall\ r \in O, t \in T, s \in S, f \in F\ (\phi^{bal}_{rtsf}) \tag{1r}$$

where all variables are contained in the set $\alpha = (x_r, g_{rtsf}, y_{tsf}, e_{rtsf}, z^{ch}_{rtsf}, z^{dch}_{rtsf}, \zeta^{cp}, u^{cp}_{sf})$. The objective function (1a) minimizes the total system cost, which includes: investment costs, $C^{inv}_r x_r$, and a weighted combination of expected operating costs (the first bracketed term) weighted by Ω, and the CVaR (the second bracketed term) weighted by $1 - \Omega$. The CVaR formulation follows the standard approach described in prior work (Munoz et al., 2017). This term represents the expected operating costs in the Ψ-worst tail of the distribution of future costs. This is modeled using the commonly used constraint (1h), which constrains the CVaR to the highest-cost Ψ tail. The auxiliary variable ζ^{cp} takes on the value of the Ψ-percentile Value-at-Risk (VaR) in the optimal solution (Rockafellar and Uryasev, 2002).

Eq. (1i) represents hourly power balance accounting for generation, load shedding, and the discharging and charging of storage technologies, respectively, z^{dch}_{rtsf} and z^{ch}_{rtsf}. Expressions (1k)–(1r) represent storage technologies, for which we follow the approach in the GenX model to demonstrate our model's ability to accommodate the storage formulation of a widely used open-source model (MIT Energy Initiative and Princeton University ZERO lab, 2023). Energy stored, e_{rtsf}, is dependent on its state in the previous period (1l); the first and last time periods are similarly linked in (1k)[4] to account, in a simplified way, for the fact that a storage operator would look beyond the last time step of a given period. Constraint (1m) states that the storage technology cannot store more energy than its energy capacity, which is the product of the built power capacity x_r and an exogenous energy-to-power ratio $\frac{1}{N^s_r}$, as commonly formulated. Charging and discharging are constrained by the available power capacity x_r in (1n), (1o), and (1r), and energy capacity in (1q).

2.3. Generation expansion with missing risk markets

Here, we model a power system without risk markets by separately formulating the optimization problems to be solved by investors and by a system operator in charge of power market dispatch. The system operator's problem is a general representation of market clearing in liberalized power markets. In our context, the system operator acts on behalf of consumers and minimizes their costs. This formulation is a close analogue of the one by Ehrenmann and Smeers (2011). Below, we first show each agent's optimization problem before introducing our approach to solving the generation expansion problem with missing markets.

2.3.1. System operator's optimization problem

The system operator solves the following linear optimization problem for each scenario. The problem is to meet inelastic electricity demand by dispatching all resources in the least cost way. The system operator's variables are contained in set $\alpha^{iso} = (g_{rtsf}, y_{tsf}, z^{ch}_{rtsf}, z^{dch}_{rtsf}, e_{rtsf})$.

$$\min_{\alpha^{iso}} \sum_t W_t \sum_r C^{var}_{rf} g_{rtsf} + \sum_t W_t C^{cap} y_{tsf} \quad \forall\ s \in S, f \in F \tag{2a}$$

$$\text{s.t.} \quad (1c), (1d), (1e), (1i)\text{–}(1r) \tag{2b}$$

where objective function (2a) minimizes operating costs (equivalent to maximizing welfare given our inelastic demand assumption), subject to the supply–demand balance constraint (1i), and the remaining physical operating constraints on generation and storage.

2.3.2. Investors' optimization problem

We define an investor agent for each technology $r \in R$, a common approach (Ehrenmann and Smeers, 2011; Mays et al., 2019). Thus, each investor considers a single technology and cannot benefit from possible diversification effects from investing in multiple technologies. As a sensitivity test, we also introduce a "representative investor" agent that invests in all technologies. We show how this can be formulated in Appendix B, discuss its implications in Section 3.6 and report its computational performance in Appendix D. For our main formulation shown below, we proceed with the common one-investor-one-technology formulation to stay consistent with previous literature.

Each investor solves the following linear optimization problem. Investors maximize a weighted combination of expected profits and the CVaR. The weighting in question is done by parameter Ω, which effectively represents the degree of risk aversion.

$$\max_{\alpha^{inv}} \ \Omega\left[\sum_s \sum_f P_{sf}\pi_{rsf}x_r - C^{inv}_r x_r\right] \\ + (1-\Omega)\left[\zeta_r - \frac{1}{\Psi}\sum_s \sum_f P_{sf}u_{rsf}\right] \quad \forall\ r \in R \tag{3a}$$

$$\text{s.t.} \quad x_r \ge 0 \quad \forall\ r \in R \tag{3b}$$

$$u_{rsf} \ge \zeta_r - \pi_{rsf}x_r + C^{inv}_r x_r \quad \forall\ r \in R, s \in S, f \in F\ (\theta_{rsf}) \tag{3c}$$

$$u_{rsf} \ge 0 \quad \forall\ r \in R, s \in S, f \in F \tag{3d}$$

$$\zeta_r \in \mathbb{R} \quad \forall\ r \in R \tag{3e}$$

where the investor's variables are contained in set $\alpha^{inv} = (x_r, \zeta_r, u_{rsf})$. The second bracketed term in (3a), weighted by $1 - \Omega$, represents the investor's CVaR. The CVaR is modeled as in Mays et al. (2019), using constraint (3c),[5] which constrains it to the Ψ-worst tail of the profit distribution, as well as the auxiliary variables ζ_r, which equals the Ψ-VaR in the optimal solution, as shown by Ehrenmann and Smeers (2011). π_{rsf} denotes revenues net of variable costs (hereafter, referred to as revenues). Revenues are defined differently for generation and storage technologies. The revenue expression for generation is the standard formulation used in prior work (Ehrenmann and Smeers, 2011; Mays et al., 2019). Specifically, revenues are defined as the dual μ_{rtsf} of the capacity limit constraint (1j) adjusted for the technologies availability A_{rt}. As stated by Ehrenmann and Smeers (2011), this expression represents the marginal value of capacity, which follows from duality theory. The economic interpretation can be gleaned from KKT condition (C.2a) in Appendix C, which relates μ_{rtsf} to the power price and the variable cost.

$$\forall\ r \in G,\ \pi_{rsf} := \sum_t \mu_{rtsf} A_{rt}$$

Storage revenues can similarly be represented using the dual values corresponding to the market value of storage. Revenues in this context represent the marginal value of installing an additional unit of capacity. This can be obtained by deriving the KKT conditions of the optimization problem (1) associated with the storage capacity variable $x_r\ \forall\ r \in O$. For ease of exposition, we show this in the risk-neutral case, $\Omega = 1$, where the KKT derivation yields: $C^{inv}_r - \sum_s \sum_f P_{sf} \sum_t W_t(\frac{1}{N^s_r}\phi^{cap}_{rtsf} +$

[4] The model implementation links the first and last hour of each representative day.

[5] Note that the investor's CVaR formulation differs from the central planner's in model (1), which is because the former maximizes profit while the latter minimizes cost.

$\phi^{c}_{rtsf} + \phi^{d}_{rtsf} + \phi^{bal}_{rtsf}) \geq 0$ (this is equivalent to KKT condition (C.1a)). The KKT condition relates the cost a unit of capacity, C^{inv}_r to its total expected value (i.e., revenues in our context). ϕ^{cap}_{rtsf}, as the dual of (1m), represents the value of additional energy storage capacity (since in our formulation the power capacity determines the energy capacity as well), while the remaining terms refer to the values of charging and discharging. It follows that total storage revenues can be defined as:

$$\forall\, r \in O,\ \pi_{rsf} := \sum_t \left[\frac{1}{N^s_r} \phi^{cap}_{rtsf} + \phi^{c}_{rtsf} + \phi^{d}_{rtsf} + \phi^{bal}_{rtsf} \right]$$

2.3.3. Generation expansion problem and numerical approaches

The problems (2) and (3) together encompass the power system generation expansion problem for a perfectly competitive, energy-only market. This problem is equivalent to model (1) in a risk-neutral case, $\Omega = 1$, where risk trading is irrelevant.[6]

To solve problem (2)–(3), a common approach is to formulate a mixed complementarity problem containing the KKT conditions of both problems (Gabriel et al., 2013). This approach results in a non-linear and non-convex problem, which can be solved, for example, using the PATH solver or a non-linear solver (Pineda et al., 2018). In problems featuring power market dispatch over many periods, as in our case, this method results in a large number of bilinear terms (i.e., the product of two continuous variables), which present a computational challenge. Recent work has developed specialized algorithms to solve problems such as ours (Hoschle et al., 2018; Mays et al., 2019), which can handle large case studies but do not guarantee convergence.

Here, we set out to develop a non-algorithmic approach. The purpose of this is twofold: first, if a problem can be formulated as a mixed integer program, this facilitates additional numerical tests that can address the multiple equilibrium problem inherent to such models, as discussed further in Section 2.7; second, a formulation that can be solved with available solvers can be more readily integrated into bi-level optimization models in future research. Non-algorithmic approaches include using big-M constraints to reformulate the KKT complementarities (Fortuny-Amat and McCarl, 1981) or SOS1variables (Siddiqui and Gabriel, 2013). However, these strategies result in a large number of binary variables and can have associated computational issues, which make modeling energy storage difficult.

To address the above challenges, we introduce a primal–dual version of the equilibrium problem, which uses the Strong Duality (SD) theorem. This formulation consists of the primal constraints, dual constraints, and SD equalities corresponding to each agent's optimization problem (Ruiz et al., 2012). Each agent's primal–dual problem is necessary and sufficient for the optimal solution to that agent's optimization problem since the latter (i.e., each of (2) and (3)) is a linear program when considered on its own. Similarly, the primal–dual problem of each agent is equivalent to that agent's KKT conditions, shown in Appendix C. Below, we introduce the primal–dual formulation of problem (2)–(3).

2.4. Equilibrium model of generation expansion with missing markets

2.4.1. System operator's primal–dual problem

In the following, (4a) is the SD condition for the system operator's optimization problem (2). Expressions (4b)–(4k) are the dual feasibility constraints, and (4l) contains the primal feasibility constraints.

$$\sum_t W_t \sum_r C^{var}_{rf} g_{rtsf} + \sum_t W_t C^{cap} y_t =$$

$$\sum_t \lambda_{tsf} D_{ts} - \sum_r \pi_{rsf} x_r \quad \forall\, s \in S, f \in F \tag{4a}$$

$$\lambda_{tsf} \in \mathbb{R} \quad \forall\, t \in T, s \in S, f \in F \tag{4b}$$

$$\mu_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{4c}$$

$$\phi^{soc}_{rtsf} \in \mathbb{R} \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{4d}$$

$$\phi^{cap}_{rtsf}, \phi^{c}_{rtsf}, \phi^{d}_{rtsf}, \phi^{bal}_{rtsf}, \xi^{d}_{rtsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{4e}$$

$$W_t C^{var}_{rf} - \lambda_{tsf} + \mu_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{4f}$$

$$W_t C^{cap} - \lambda_{tsf} \geq 0 \quad \forall\, t \in T, s \in S, f \in F \tag{4g}$$

$$\phi^{soc}_{rtsf} - \phi^{soc}_{rt+1sf} + \phi^{cap}_{rtsf} - \xi^{d}_{rt+1sf} \geq 0$$

$$\forall\, r \in O, t \in \{1, 2, \ldots, |T| - 1\}, s \in S, f \in F \tag{4h}$$

$$\phi^{soc}_{r|T|sf} - \phi^{soc}_{r1sf} + \phi^{cap}_{r|T|sf} - \xi^{d}_{r1sf} \geq 0 \quad \forall\, r \in O, s \in S, f \in F \tag{4i}$$

$$-F^{ch} \phi^{soc}_{rtsf} + \phi^{c}_{rtsf} + \phi^{bal}_{rtsf} + \lambda_{tsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{4j}$$

$$\frac{1}{F^{dch}} \phi^{soc}_{rtsf} + \phi^{d}_{rtsf} + \xi^{d}_{rtsf} + \phi^{bal}_{rtsf} - \lambda_{tsf} \geq 0$$

$$\forall\, r \in O, t \in T, s \in S, f \in F \tag{4k}$$

$$\text{(1c), (1d), (1e), (1i)–(1r)} \tag{4l}$$

Expressions (4f) and (4g) are the stationarity conditions that hold for the optimal dispatch of generation technologies and load shedding respectively. Expressions (4h) and (4i) determine the optimal amount of energy stored in each storage technology, with the latter accounting for the relationship between the first and last time period. Expressions (4j) and (4k) relate to the optimal charging and discharging decisions respectively. Note that this problem contains non-convex bilinear terms $\pi_{rsf} x_r$ in (4a). We address this in Section 2.6.

2.4.2. Investors' primal–dual problem

In the following, (5a) is the SD equality for the investors' problem (3). Note that the dual objective is zero. Expressions (5b)–(5d) represent the dual feasibility constraints, and (5e)–(5i) are the primal feasibility constraints of the investors' optimization problems (3). Note that the derivation included multiplying $1 - \Omega$ by both sides of constraint (3c).

$$\Omega \left[\sum_s \sum_f P_{sf} \pi_{rsf} x_r - C^{inv}_r x_r \right]$$

$$+ (1 - \Omega) \left[\zeta_r - \frac{1}{\Psi} \sum_s \sum_f P_{sf} u_{rsf} \right] = 0 \quad \forall\, r \in R \tag{5a}$$

$$C^{inv}_r - \sum_s \sum_f (\Omega P_{sf} + (1 - \Omega) \theta_{rsf}) \pi_{rsf} \geq 0 \quad \forall\, r \in R \tag{5b}$$

$$\frac{1}{\Psi} P_{sf} - \theta_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{5c}$$

$$\sum_s \sum_f \theta_{rsf} = 1 \quad \forall\, r \in R \tag{5d}$$

$$u_{rsf} \geq \zeta_r - \pi_{rsf} x_r + C^{inv}_r x_r \quad \forall\, r \in R, s \in S, f \in F \tag{5e}$$

$$x_r \geq 0 \quad \forall\, r \in R \tag{5f}$$

$$u_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{5g}$$

$$\zeta_r \in \mathbb{R} \quad \forall\, r \in R \tag{5h}$$

$$\theta_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{5i}$$

Expression (5b) represents the stationarity condition of the investor problem (3), corresponding to optimal investment decisions x_r. (5c) and (5d) are the stationarity conditions found from differentiating the investors' optimization problems with respect to u_{rsf} and ζ_r, respectively. As in prior work, θ_{rsf} represents the risk-adjusted probability for scenarios in the probability distribution tail defined by parameter Ψ (Ehrenmann and Smeers, 2011).

[6] The KKT conditions of (2) and (3) are shown in Appendix C. A trivial derivation of the KKT conditions of problem (1) can confirm they are equivalent to the KKT conditions of (2) and (3) when $\Omega = 1$. In the risk-averse case, $\Omega \in [0, 1)$, the two problems are no longer equivalent, which has to do with whether markets for risk are implicitly complete as in (1) or missing as in (2)–(3).

Table 1
Properties of risk-adjusted probability variable θ_{rsf} These properties refer to the values of θ_{rsf} before making Assumptions 1 and 2.

	Definition	θ_{rsf}	u_{rsf}
In CVaR tail	$\pi_{rsf}x_r - C_r^{inv}x_r \le \zeta_r$	$0 \le \theta_{rsf} \le \frac{1}{\Psi}P_{sf}$	$u_{rsf} \ge 0$
Not in CVaR tail	$\pi_{rsf}x_r - C_r^{inv}x_r > \zeta_r$	$\theta_{rsf} = 0$	$u_{rsf} = 0$

Note that problem (5) presents additional challenges for numerical solutions because of the bilinear terms $\theta_{rsf}\pi_{rsf}$ in (5b), as well as the bilinear terms $\pi_{rsf}x_r$ in (5a) and (5e).

Our purpose is to solve the entire equilibrium primal–dual model of generation expansion (4)–(5). This model is non-convex due to the mentioned bilinear terms. We attempted to solve this problem with Gurobi's non-convex algorithm (Gurobi, 2020) but did not find this to be tractable, as the solver fails to find a solution before reaching a termination threshold of 10 h.[7] To make the problem tractable, we first introduce an exact linear reformulation of the bilinear terms $\theta_{rsf}\pi_{rsf}$ in (5b) in the following section.

2.5. Exact linear reformulation for the risk-averse investment problem's bilinear terms $\theta_{rsf}\pi_{rsf}$

Here, we introduce our method for handling the bilinear terms $\theta_{rsf}\pi_{rsf}$ in (5b) through an exact linear reformulation that leads to a lower computational burden. Ultimately, the task we set out to accomplish is to show that, under mild assumptions formalized below, the continuous variable θ_{rsf} can be replaced by a product of a binary and a constant. We start by setting down necessary notation. The set of all scenarios is $S \times F$ with P_{sf} the probability of each scenario (s,f) and cardinality $|S \times F| := N^{all}$. Furthermore, we formalize the set of scenarios in the CVaR tail with the following definition.

Definition 1. Let V be the set of scenarios in the CVaR tail; $V \subset S \times F$, with cardinality $|V| := N^{cvar}$. Formally, $\forall\,(s,f) \in V, \pi_{rsf}x_r - C_r^{inv}x_r \le \zeta_r$. Equivalently, $\pi_{rsf}x_r - C_r^{inv}x_r > \zeta_r\ \forall\,(s,f) \notin V$.

Next, we explore the properties of θ_{rsf} across the different scenarios (summarized in Table 1). Recall that θ_{rsf} is the risk-adjusted probability that a risk-averse investor places on scenario (s,f). As shown by Ehrenmann and Smeers (2011), θ_{rsf} has the following property for scenarios outside of the CVaR tail:

Remark 1. $\theta_{rsf} = 0\ \forall\ (s,f) \notin V$. To see this, note that from Definition 1, $\forall\,(s,f) \notin V, \pi_{rsf}x_r - C_r^{inv}x_r > \zeta_r$, which implies $\theta_{rsf} = 0$ by the KKT condition (C.1d). Further note this implies $u_{rsf} = 0$ by KKT condition (C.1b).

Next, for scenarios in the CVaR tail, there are two possibilities (Ehrenmann and Smeers, 2011). First, if $\pi_{rsf}x_r - C_r^{inv}x_r < \zeta_r$, then $u_{rsf} > 0$ by (C.1d), and $\theta_{rsf} = \frac{P_{sf}}{\Psi}$ by (C.1b). Second, if $\pi_{rsf}x_r - C_r^{inv}x_r = \zeta_r$, u_{rsf} is not necessarily strictly positive, leading to: $0 \le \theta_{rsf} \le \frac{P_{sf}}{\Psi}$. This makes our task challenging, so, to impose stricter boundary conditions on θ_{rsf}, we introduce the following mild assumptions.

Assumption 1. The probability mass function for scenarios $S \times F$ in problem (3) follows a discrete uniform distribution with probability $P_{sf} = P\ \forall\,(s,f)$, where $P = \frac{1}{N^{all}}$.

Note that Assumption 1 is without loss of generality because a non-uniform distribution can be accommodated using scenario copies.

Assumption 2. $\Psi \in \{cP : c \in \{1,2,\dots,N^{all}\}\}$, i.e., Ψ is a discrete probability that only takes on integer multiples of P.

These assumptions allow us to use the number of scenarios in the CVaR tail, N^{cvar}, to describe the probabilities θ_{rsf}. First note that:

Lemma 1. *$N^{cvar}P = \Psi$ under Assumptions 1 and 2. Proof: Recall that N^{cvar} is the number of scenarios in the CVaR tail, per Definition 1, and that Ψ is the cumulative probability of this tail. If all scenarios have equal probability P, per Assumption 1, it follows that Ψ is a multiple of P. Since N^{cvar} is an integer while Ψ is not necessarily an integer, $N^{cvar}P \ge \Psi$. However, if we assume that Ψ is an integer multiple P, i.e., Assumption 2, it follows that $N^{cvar}P = \Psi$.*

Given Lemma 1, we next show that all θ_{rsf} in the CVaR tail are equal under the above assumptions.

Proposition 1. *$\theta_{rsf} = \frac{1}{N^{cvar}}\ \forall\ (s,f) \in V$. Proof: given Lemma 1, we can replace Ψ with $N^{cvar}P$ in (5c). This leads to: $\theta_{rsf} \le \frac{1}{N^{cvar}}$. Further, note that, since all θ_{rsf} sum to one by (C.1c), and since θ_{rsf} outside the CVaR tail are zero, by Remark 1, then the θ_{rsf} in the CVaR tail sum to one; i.e., $\sum_{(s,f)\in V}\theta_{rsf} = 1$. This equality can be rewritten as: $\sum_{(s,f)\in V}\theta_{rsf} = N^{cvar}\frac{1}{N^{cvar}}$. Given that $\theta_{rsf} \le \frac{1}{N^{cvar}}$, the equality $\sum_{(s,f)\in V}\theta_{rsf} = N^{cvar}\frac{1}{N^{cvar}}$ holds only if $\theta_{rsf} = \frac{1}{N^{cvar}}\ \forall\,(s,f) \in V$.*

Based on Proposition 1, we can introduce our exact substitution for the continuous variable θ_{rsf} as follows:

Proposition 2. *$\theta_{rsf} = \frac{1}{N^{cvar}}\theta^Z_{rsf}\ \forall\ (s,f) \in S \times F$, where $\theta^Z_{rsf} \in \{0,1\}\ \forall\ r,s,f$. Proof: $\theta_{rsf} = 0\ \forall\ (s,f) \notin V$ by Remark 1. $\theta_{rsf} = \frac{1}{N^{cvar}}\ \forall\ (s,f) \in V$ by Proposition 1. Therefore, θ_{rsf} can be exactly replaced by $\frac{1}{N^{cvar}}\theta^Z_{rsf}$. As a remark, the auxiliary binary variable θ^Z_{rsf} has the following properties: $\theta^Z_{rsf} = 1\ \forall\,(s,f) \in V$, and $\theta^Z_{rsf} = 0\ \forall\,(s,f) \notin V$.*

For the rest of the paper we assume that Assumptions 1 and 2 hold. Given Proposition 2, we can exactly reformulate the investor's problem using the following two steps. First, we introduce constraints (6a), (6b), (6c), and (6d), which replace respectively, (5i), (5c), (5d), and (5b).

$$\theta^Z_{rsf} \in \{0,1\} \quad \forall\, r \in R, s \in S, f \in F \tag{6a}$$

$$\frac{1}{\Psi}P_{sf} - \frac{1}{N^{cvar}}\theta^Z_{rsf} \ge 0 \quad \forall\, r \in R, s \in S, f \in F \tag{6b}$$

$$\sum_s \sum_f \frac{1}{N^{cvar}}\theta^Z_{rsf} = 1 \quad \forall\, r \in R \tag{6c}$$

$$C_r^{inv} - \Omega\sum_s\sum_f P_{sf}\pi_{rsf} - (1-\Omega)\sum_s\sum_f \frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf} \ge 0 \quad \forall\, r \in R \tag{6d}$$

Second, we introduce an exact substitution for $\frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf}$ in (6d) by adapting a standard technique (Tanaka et al., 2022, e.g.), which is to introduce constraints (7a)–(7f) where $\bar{M}$ is a sufficiently large upper bound.[8] The linear expression (7f) replaces the non-convex expression (6d). The justification for this substitution is that v_{rsf} exactly matches $\frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf}$.[9]

$$v_{rsf} \ge 0 \quad \forall\, r \in R, s \in S, f \in F \tag{7a}$$

[7] The model was run on a cluster with specifications described in Appendix D.

[8] The value of this upper bound can be based on the observation that each technology's revenues are upper-bounded by its investment cost by construction via (5b).

[9] To see why note that if $\theta^z_{rsf} = 1$, then $h_{rsf} = 0$, leading to $v_{rsf} = \frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf}$; and if $\theta^z_{rsf} = 0$, then $v_{rsf} = 0 = \frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf}$. If $\theta^z_{rsf} = 0$, then $h_{rsf} = \frac{1}{N^{cvar}}\pi_{rsf}$. Note that this does not affect the solution as h_{rsf} is not used elsewhere in the model.

$$h_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{7b}$$

$$v_{rsf} \leq \bar{M}\theta^{Z}_{rsf} \quad \forall\, r \in R, s \in S, f \in F \tag{7c}$$

$$h_{rsf} \leq \bar{M}(1 - \theta^{Z}_{rsf}) \quad \forall\, r \in R, s \in S, f \in F \tag{7d}$$

$$v_{rsf} + h_{rsf} = \frac{1}{N^{cvar}}\pi_{rsf} \quad \forall\, r \in R, s \in S, f \in F \tag{7e}$$

$$C^{inv}_r - \Omega \sum_s \sum_f P_{sf}\pi_{rsf} - (1-\Omega)\sum_s \sum_f v_{rsf} \geq 0 \quad \forall\, r \in R \tag{7f}$$

We can now introduce the following exact reformulation of the investor's problem:

Proposition 3. *The solution set of the problem containing (5a), (5e)–(5h), (6a)–(6c), and (7) is the same as the solution set of problem (5), for a sufficiently large $\bar{M}$, and under Assumptions 1 and 2. Proof: The problem containing (5a), (5e)–(5h), (6a)–(6c), and (7) is algebraically equivalent to (5) under Proposition 2, which is derived from KKT conditions (C.1b), (C.1c), and (C.1d). These KKT conditions necessarily hold for the solution of (3), which is equivalent to the solution of (5) since (3) is a linear program.*

The combination of the system operator's problem (4) and the new investor problem, containing (5a), (5e)–(5h), (6a)–(6c), and (7), represents the generation expansion problem (8), which is our main model. Formulation (8) is equivalent to the original problem (4)–(5) under the premise and result of Proposition 3.

(4), (5a), (5e)–(5h), (6a)–(6c), (7)   (8)

2.6. Solution approaches to equilibrium generation expansion problem

Model (8) is non-convex due to the remaining bilinear terms $\pi_{rsf}x_r$ in (5a), (5e), and (4a). This non-convexity can be addressed in several different ways. First, we find that model (8) can be solved as a mixed integer quadratically constrained program (MIQCP) with Gurobi's non-convex solver (Gurobi, 2020). This solver uses McCormick relaxation and spatial Branch and Bound. Second, the bilinear terms $\pi_{rsf}x_r$ can be approximated by adapting the piece-wise linearization method by Gabriel et al. (2006), which can be used to reformulate our problem as a mixed integer linear program. Third, the bilinear terms $\pi_{rsf}x_r$ can be linearized by discretizing the capacity variable and performing binary expansion as shown by Wogrin et al. (2013). After testing these methods, we find the first approach outperforms the others in solution speed, and use it in this paper.

2.7. Numerical robustness procedure

An important property of risk-averse equilibrium models is the possibility of multiple equilibria (Gérard et al., 2018). We do not rule this out in the case of our model and leave the task of proving uniqueness for future work. However, we introduce a numerical procedure to test the robustness of our results, which takes advantage of the fact that our model can be solved via integer programming. The procedure entails solving a new optimization problem, which solves our equilibrium problem while optimizing for a given linear objective function. The procedure is thus analogous to modeling to generate alternatives (DeCarolis, 2011). Here, we construct the following optimization model, which minimizes a linear objective function equal to expected emissions, (9a), while solving the original problem, (9b), therefore forming a MIQCP.

$$\min \quad \sum_s \sum_f P_{sf} \sum_t W_t E^{co2}_r g_{rtsf} \tag{9a}$$

$$\text{s.t.} \quad (8) \tag{9b}$$

The choice of this objective function is motivated by our main research questions, which concern the level of emissions in different cases. We are especially interested in solutions with emission outcomes that refute our main result that the missing market problem increases emissions. Since this MIQCP model can be solved via integer programming to global optimality using Gurobi's non-convex solver (Gurobi, 2020), the solution represents the lowest-emission solution from among the possible equilibria. If this solution contains higher emissions than with complete markets, we can conclude that our findings regarding the impact of missing markets on emissions are not affected by the possibility of other equilibria. As discussed in Section 3.5, we find this to be the case. Note that this procedure can be extended to search for all emission solutions by also running (9) with a maximization objective.

Table 2
Alternative risk cases.

Case	Model	Risk aversion setting
Risk-neutral	(1)/(8)	$\Omega = 1$
Risk-averse & missing markets	(8)	$\Omega = 0.5$
Risk-averse & complete markets	(1)	$\Omega = 0.5$

2.8. Experimental design

To address our research questions, we construct three cases (Table 2). Our main case, labeled "risk-averse & missing markets", models a power system with risk-averse agents and missing risk markets, and is computed using our main model, (8). For the purpose of our first research question, we also construct a "risk-neutral" case where all agents are risk-neutral. Note that the risk-neutral case can be interpreted as featuring missing risk markets[10]; thus, by comparing it to the "risk-averse & missing markets" case, we can assess the effects of investment risk on the power system. To address our second research question, regarding how an absence of risk markets impacts the power system, we compare the "risk-averse & missing markets" case to a "risk-averse and complete markets" case. The latter case represents the socially optimal outcome with complete long-term markets between risk-averse investors and risk-averse consumers. Note that the consumers implicitly represented in the "risk-averse & missing markets" case can also be interpreted as risk-averse.[11] Therefore, the only difference between these cases is the availability of risk trading. The complete market case is generated with model (1).

We model an abstract power system including four technologies: gas plants (combined cycle combustion), onshore wind, solar photovoltaic, and 4-h Li-ion batteries. Albeit highly simplified, this case study captures several key features shared by low-carbon power systems: an emitting dispatchable technology with relatively low capital intensity (gas), zero-carbon technologies with high capital intensity and variable capacity factors (wind and solar), and energy storage. A sensitivity test including a baseload technology, which can be interpreted as subsidized nuclear, does not alter our findings (see Section 3.6).

Technology cost data is sourced from the NREL (2022) "moderate" scenario for 2030 and shown in Table 3, except for the investment cost of the 4-h battery, which is based on the NREL (2022) "advanced" scenario. We chose this cost scenario to ensure that the battery technology will feature in our model solutions. This means that our experiments can either be interpreted as representing a future of additional cost declines or one in which batteries continue to receive a certain level of subsidies. As is common, the investment costs in the models, C^{inv}_r, represent annualized costs, which we calculated based on the CAPEX shown in Table 3 and a risk-free discount rate of 2% (since risk is

[10] The risk-neutral case can be equivalently interpreted as featuring missing or complete risk markets and can be modeled with either the equilibrium or optimization models.

[11] Consumers in this case can be equivalently interpreted as risk-averse or risk-neutral because their decisions, as represented by the system operator, lack any first-stage variables that can be influenced by risk.

Table 3
Technology parameters.

	CAPEX ($/kW)	Variable cost ($/MWh)	Emissions intensity (tCO_2/MWh)
Gas (combined cycle)	912	30	0.4
Onshore wind	950	0	0
Solar PV	752	0	0
Batteries (4-h)	680	0	0

modeled endogenously). The annualized investment costs are shown in Table 4 (second column). The variable cost of gas assumes a gas price of $3.8/MMBtu (EIA, 2022a), a heat rate and variable O&M costs from NREL (2022), as well as a CO_2 cost based on a $10/$tCO_2$ carbon price (RGGI Inc., 2023) and a 0.4 tCO_2/MWh emissions intensity (EIA, 2022b). Time series for electricity demand and renewable capacity factors are for the New England power system and are sourced from Dimanchev et al. (2021). The power market's price cap,[12] C^{cap}, is assumed to be $2000/MWh, motivated by the offer cap in the New England power system. This is a simplification since power prices can in reality rise above the offer cap. Another simplification inherent in our model is that we omit capacity market revenues. The Supplementary Materials provide results based on alternative values of $9000/MWh and $100/MWh, which do not change the directionality of our emissions results.

We represent the power system's operation using 30 representative days at an hourly resolution, leading to 720 time steps. Though simplified, this temporal scope captures the limitations that variability imposes on wind and solar (Mallapragada et al., 2020; Reichenberg et al., 2018). Sensitivity tests using a full year with 8760 time steps did not change the directionality of our main results, which concern how the capacity mix and emissions change across different representations of risk (see the Supplementary Material). Thus, the use of 30 days can be deemed sufficient for our purpose, which is to illustrate the system's behavior, rather than to predict market outcomes. Each hour is scaled using weights W_t so that the entire 30-day period represents one year. The 30-day time series (for demand and renewable availability) and their weights W_t are generated using the K-means clustering method in the GenX model, which is configured to capture extreme periods (MIT Energy Initiative and Princeton University ZERO lab, 2023).

The experiments consider two sources of uncertainty. These are represented in a simplified way with two scenarios each, as our purpose is only exploratory. First, demand uncertainty is represented with two scenarios, contained in set S, featuring a "high" and "low" level of demand that scale load higher and lower by 25% (while keeping hourly variations the same). The 25% variation was chosen as roughly illustrative of the degree to which long-term load varies across electrification scenarios modeled in prior work (Larson et al., 2020). Second, gas price uncertainty, set F, includes two scenarios featuring a gas price that is 25% higher and lower respectively relative to the aforementioned price assumption. The magnitude of this price variation was chosen only for illustration of possible future variability. The main results presented below were derived from modeling both uncertainties (four total scenarios). Results from modeling each uncertainty separately are also presented in Appendix A. Though policy risk is not the focus of this paper, we note that the gas price stochasticity can also be interpreted as carbon price stochasticity since gas is the only emitting technology in our experiments. Risk aversion is parameterized using $\Omega = 0.5$[13] and $\Psi = 0.25$ across all models. These values are chosen for illustrative purposes. The Supplementary Materials report sensitivity tests, which do not alter our conclusions.

[12] The price cap in our model represents in effect the model's Value of Lost Load.

[13] This value could be interpreted as 50% of financing being provided by risk-neutral equity investors and 50% by risk-averse debt investors, similarly to the interpretation suggested by Mays and Jenkins (2023).

3. Results and discussion

To understand how the missing market problem impacts the power system, we first analyze technologies' risk exposures in the absence of risk markets and the effects of risk on technologies' costs (Section 3.1). Then, we turn to the implications of the missing market problem for investments (Section 3.2) and emissions (Section 3.3).

3.1. Impact of risk exposure on technology costs

Here, we analyze the power system outcome in our main "risk-averse & missing markets" case (Table 2). Recall that we model uncertainty in demand and the gas price with two scenarios each, for a total of four scenarios, which all have equal probability of 25%. The risk faced by each technology can be described via the distribution of its revenues across the four scenarios, as generated by the model. We display all distributions in Fig. 1. The figure shows that the gas plant is exposed to a relatively wide revenue distribution. Gas earns zero revenues in two of the scenarios, where its marginal cost sets the electricity price. These scenarios correspond to low electricity demand. In the other two scenarios (which correspond to high electricity demand), the gas plant receives relatively large revenues. This illustrates how gas investors rely on revenues earned during rare periods of scarcity pricing when the electricity prices rises above their marginal cost. Scarcity pricing occurs in our model during periods of load shedding, which occurs only in the high demand scenarios. It is particularly noteworthy that the battery technology also exhibits a large variance in revenues. This is similarly due to batteries relying heavily (though not exclusively) on scarcity pricing revenues.

Fig. 1 further shows that wind and solar revenues do not vary as widely across scenarios compared to gas, as these technologies earn money across scenarios. This is due to the fact that wind and solar are infra-marginal in the merit order, which allows them to earn revenues when gas is on the margin (as expected, there are also periods when renewables are on the margin and the price is zero). The distribution for wind is wider than for solar, which is due to the greater coincidence between wind availability and periods of scarcity (i.e., high load net of renewable generation).

We next consider how risk influences technologies' investment costs (Table 4). Note that each technology's expected revenues represent the required return on investment given its risk. In equilibrium, the return on investment equals the investment cost inclusive of risk. Therefore, a technology's actual risk-reflective investment cost can be found by computing the expected value of its revenues across all scenarios (which were shown in Fig. 1), as discussed by Mays and Jenkins (2023). Table 4 displays the resulting investment costs (third column). For comparison, the table also shows the exogenous risk-free investment cost (second column), based on the assumed risk-free rate (first column).[14] From the values in the first three columns, we can derive the WACC resulting from each technology's risk exposure. This is done by solving for the WACC necessary to increase the investment cost from the risk-free value (second column) to the risk-adjusted value (third column), following prior work Mays and Jenkins (2023). Finally, the fifth and sixth columns in the table show the impact of risk on a technology's costs in terms of the risk premium and the overall increase in investment cost respectively.

The results in Table 4 show that the gas plant's investment cost is most strongly affected by risk (sixth column), followed by the battery,[15] wind, and solar. Wind and solar costs are less affected by risk than

[14] The risk-free rate and the resulting investment cost are both inputs to our modeling as opposed to the endogenous investment cost, which is an output.

[15] The battery's risk premium is larger than the gas plant's but its investment cost is affected less due to the battery's shorter economic lifetime of 20 years compared to 30 for gas.

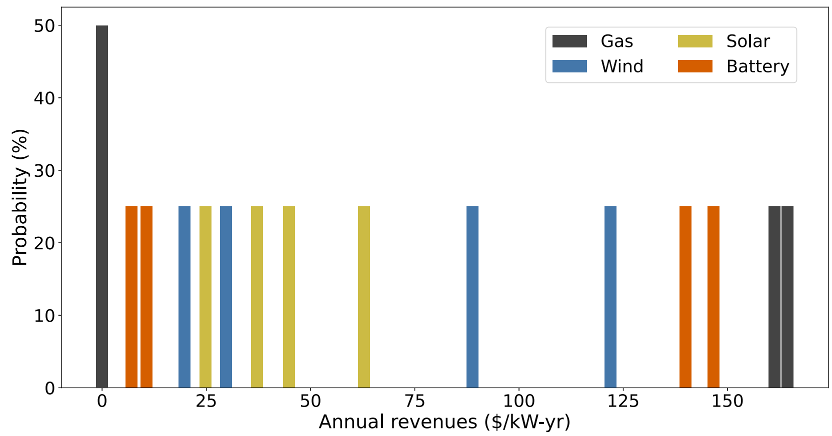

Fig. 1. Probability distributions of technology revenues. Revenues represent the value of expression π_{rsf} from the "risk-averse & missing markets" case.

Table 4
Impact of investment risk on the cost of capital. The four rightmost columns are derived from the "risk-averse & missing markets" case.

	A Risk-free discount rate (%)	B Investment cost risk-free ($/kW-yr)	C Investment cost risk-adjusted ($/kW-yr)	D WACC (%)	D-A Risk premium (% point)	(C-B)/B Investment cost change (%)
Gas	2	41	81	8	6	100
Wind	2	42	65	5	3	53
Solar	2	34	42	4	2	26
Battery	2	42	76	9	7	83

Table 5
Impact of investment risk on technologies' total costs. Results derived from the "risk-averse & missing markets" case.

	LCOE, risk-free ($/kWh)	LCOE risk-adjusted ($/kWh)	Change (%)
Gas	0.058	0.086	48.3
Wind	0.013	0.019	46.2
Solar	0.023	0.029	26.1

gas, in line with results by Mays and Jenkins (2023). Comparing the two renewable technologies, we observe that wind exhibits a larger risk premium. The difference is driven by the greater variance in wind revenues discussed above.

Out of the two sources of risk, it is the demand stochasticity that mainly drives the risk premia shown in Table 4. If we assume a constant gas price and only model demand uncertainty, we estimate similar WACC values of 8%, 5%, 3% and 9% for gas, wind, solar, and batteries respectively. As expected, gas price uncertainty does not significantly affect the gas plant risk premium, which is due to the nature of marginal cost pricing. This refers to the fact that, outside of scarcity pricing periods, gas would pass on its fuel cost to consumers. This effect has been described as a "natural hedge" for fossil fuel producers (Grubb and Newbery, 2018).

To explore the role of technologies' capital intensities, we calculate each generation technology's total costs, as measured by the expected Levelized Cost of Energy (LCOE), shown in Table 5. The first column shows the LCOE based on the risk-free investment cost, as well as technologies' capacity factor in the "risk-averse & missing markets" case, i.e., the solution of model (8). The relatively low renewable LCOEs are due to the 2% discount rate and our simplifying assumptions[16] (which do not affect our conclusions, as our results are only meant to be broadly illustrative). The second column shows the LCOE based on the endogenous investment cost inclusive of risk and the same capacity factor used for the first column.

Perhaps surprisingly, Table 5 shows that the gas technology's LCOE is more strongly impacted by risk than renewables, even though gas is less capital intensive. This result is driven by the strong impact of risk on the gas plant's investment cost (sixth column of Table 4), which outweighs the technology's low capital intensity. This finding demonstrates the importance of differentiating between technologies' risk premia.

3.2. Implications of the missing market problem for the capacity mix

Fig. 2-a shows the capacity mix in our three risk cases. By comparing the first and second columns, we find that investors' risk exposure leads to less investment in variable renewables and batteries, and more investment in gas generation. These results show that renewable and storage investments are relatively more sensitive to the risks they are exposed to compared to gas. Importantly, this is only partly due to their capital intensity. As we showed above, the renewable LCOEs are less affected by risk than the gas LCOE. This is not a generalizable result but merely an illustration that capital intensity cannot serve as a primary explanation for the way risk impacts investment. Aside from capital intensity, the observed changes reflect how technologies interact within the power system. One of the main advantages of our use of a generation expansion model is that we capture each technology's unique value to the power system. A technology's system value is determined by its capabilities and how it interacts with the rest of the system. Gas has a relatively high system value because, as the dispatchable technology in our experiments, it competes mainly with expensive load shedding and partly with relatively expensive energy storage. This means that gas investment is not very sensitive to a change in its total cost (this is further explored in our sensitivity test featuring a lower price cap and the test including a baseload technology). In contrast, the intermittency of wind and solar limits their system values and makes investments relatively more sensitive to changes in their total costs.

A somewhat surprising result is that gas capacity increases when we capture investment risk (as shown by comparing the first and second columns in Fig. 2-a). This occurs despite the negative influence of risk on the cost of gas discussed previously. The increase in gas capacity can be explained by the large decreases in other technologies, which act largely as competitors to the gas investors. As wind, solar, and battery capacities are lower in the "risk-averse & missing markets" case, this creates an additional revenue opportunity for the gas plant. This result is in part driven by our limited set of technologies, but it

[16] We omit fixed O&M costs across technologies, and assume a 30-year economic lifetime across the generation technologies.

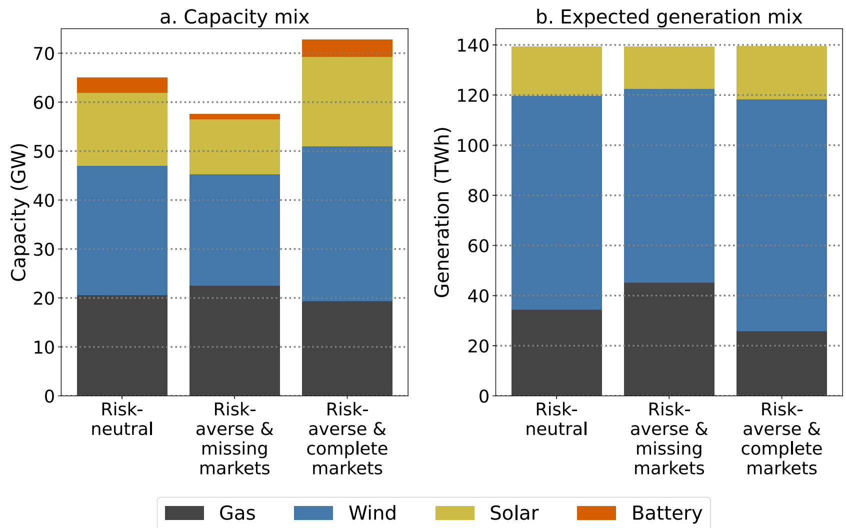

Fig. 2. Capacity and generation mix for different representations of risk. All cases include both demand and gas price stochasticity. "Risk-averse & missing markets" refers to output from model (8). The remaining cases show output from (1). Generation is computed in expectation over all scenarios.

nevertheless serves to illustrate that dispatchable technologies are able to capture greater value in a risky world. Whether this translates to increase in gas capacity in absolute terms depends on the degree to which competing technologies are impacted by risk, and is therefore highly case-dependent. The increase in gas capacity (in absolute terms) almost disappears in our sensitivity test modeling a full year (see the Supplementary Materials).

Next, to isolate the effects of risk markets, we compare the second and third columns in Fig. 2-(a). Recall that the "risk-averse & complete markets" case represents the optimal outcome in a market with risk-averse investors, risk-averse consumers, and complete long-term markets for risk (equivalently it represents the optimal decisions of a risk-averse central planner). This case exhibits more investment in wind, solar, and batteries and less investment in gas compared to the missing markets case. When markets are complete, trading of risk between consumers and investors reduces investors' risk exposure and encourages investments in the technologies that are optimal from a system's perspective. Because of the risk aversion of consumers, the market as a whole places additional emphasis on reducing the system's total operating costs in the highest-cost scenario. This can be observed in the analytical formulation of the model, specifically constraint (1h). Reducing total operating costs is accomplished by reducing load shedding and decreasing generation from sources with high variable costs (gas in our case). To do so, the power market encourages (equivalently, the central planner builds) additional variable renewables and storage capacity. What makes clean energy technologies more valuable in this case is their low variable cost, showing that their capital intensity is not necessarily a disadvantage from a system's perspective. Therefore, with regard to our second research question, these results show that the missing market problem can decrease renewable and storage investment. Previous work similarly showed less investment in wind with incomplete markets (Mays et al., 2019). We further note that the optimal risk-averse outcome entails greater clean energy investment than the risk-neutral case, which is also consistent with previous work (Munoz et al., 2017; Diaz et al., 2019), though for different sets of stochastic parameters.

3.3. Implications of the missing market problem for emissions

Table 6 shows annual power system emissions, which are calculated in expectation. The results show that emissions are higher in the missing markets case (second row) compared to the complete markets case (third row). Therefore, the missing markets problem increases emissions in our experiment. This stems from the decrease in renewable capacity observed earlier with missing markets. Decreased renewable investment leads to less renewable generation, which is replaced by gas generation (Fig. 2-b). These results hold across key sensitivities (as discussed below and shown in Figure S1 in the supplementary document). The observed emissions results indicate that the socially optimal risk-averse outcome entails lower emissions than what may result from power markets in the absence of risk trading.

Table 6
Expected CO_2 emissions.

	Emissions (MtCO2)	Emissions intensity (tCO2/MWh)
Risk-neutral	13.8	0.10
Risk-averse & missing markets	18.1	0.13
Risk-averse & complete markets	10.4	0.07

In the risk-neutral case (first row in Table 6), emissions are lower relative to the missing markets case (second row), which is also driven by the difference in renewable capacities between cases. This result aligns with prior work using agent-based modeling (Yang et al., 2023) where the authors modeled risk-averse investment, excluding storage, under carbon price uncertainty.

3.4. Implications of the missing market problem for system costs

This section considers how investment risk impacts other criteria of power system performance. Table 7 first displays the expected average system cost. This can be interpreted as a measure of the system's overall social welfare (since the model's demand curve is inelastic) from a risk-neutral government's perspective.[17] The results show that expected system costs are lower with complete markets relative to the missing markets case. This is in large part due to differences in non-served energy, and reflects the under-investment caused by the missing market problem (the relatively small cost difference is due to the use of a risk-neutral, rather than risk-averse, system cost in the table). We also note that expected costs are higher with complete markets than in the risk-neutral case. In practical terms, this reflects that the risk-averse market optimum entails an insurance cost (in the form of higher expected costs), the purpose of which is to reduce costs in the highest-cost scenario.

[17] In a risk-averse market, social welfare may also be defined to include agents' risk aversion, which we leave for future work.

Table 7
System performance for different risk cases.

	Average system cost ($/MWh)	Non-served energy (GWh)
Risk-neutral	26.05	0.2
Risk-averse & missing markets	26.43	8.2
Risk-averse & complete markets	26.35	0.0

3.5. Multiple equilibria and robustness of results

While we find that missing markets imply higher emissions, we have so far not addressed the possibility of alternative equilibrium solutions. To check for other solutions that may refute this finding, we run model (9). We find that the global minimum emissions are equivalent to the presented results from our equilibrium model (8), with the single exception of the case where we only model gas price uncertainty (last column of Table A.8). In this case, model (9) finds a different equilibrium solution with emissions of 13.2 Mt,[18] lower than the estimate we derive from our main model (8) of 14.5 Mt. The capacity mix also differs, with solar in particular exhibiting a difference of 2.6 GW. When we refer to results from this case (shown in Appendix A), we use the result derived from model (9). Note that the emissions in this solution are still higher than in the complete market and risk-neutral cases. Thus, this robustness test shows that the directions of our emissions results are not affected by the existence of multiple equilibria.

3.6. Sensitivity analysis

Here we first isolate the impact of each source of risk on the results. This is done by re-running our models with a single stochastic parameter at a time (either demand or the gas price); the results are displayed in Table A.8 in Appendix A. These tests show that both demand and gas price stochasticity, on their own, discourage overall investment in storage and in variable renewables in the "risk-averse & missing markets" case relative to both the complete markets and risk-neutral cases. We also find that the directionality of the emissions results is consistent for each source of uncertainty (Figure S1 in the supplementary document).

We also test the sensitivity of our results to the inclusion of an additional baseload technology, which is assumed to be zero-emission, fully dispatchable, and capital intensive. This technology can be interpreted, for example, as subsidized nuclear. For this technology, we use an annualized investment cost of $100/kW-yr. This value is far below the cost of nuclear estimated by NREL (2022). It is chosen for illustrative purposes to ensure that this technology features in our model's solution. We further assume an illustrative variable cost of $10/MWh. The "risk-averse & complete markets" case features capacities of: 11, 22, 9, 2, 11 GW respectively for gas, wind, solar, batteries, and the baseload technology. In comparison, the "risk-averse & missing markets" case results in capacities of: 17, 17, 6, 1, and 7 GW; and the risk-neutral case results in: 15, 20, 7, 2 and 8 GW. Therefore the addition of a baseload technology does not alter the directions in which capacities change across our cases. Emissions changes across cases also have the same directions as in our main tests (Figure S1 in the supplementary document).

Turning to the sensitivity of our results to the existence of storage, we re-run our model without the battery technology. We confirm that the changes in emissions (shown in Figure S1 in the supplementary document) and capacity between our cases have the same directions as with storage. Consistent with this result, we find that the risk premia for gas, wind, and solar are virtually the same as in the previous results featuring the storage technology.

Next, we explore the implications of modeling one technology per investor (as we do in our main model (8)) relative to using a "representative investor" agent deploying all technologies, as discussed in Section 2.3.2. Results based on a representative investor capture risk sharing between technology investments. When modeling both demand and gas price uncertainty, we observe the same results as with our main model. This equivalence occurs because, in our case study, all technologies happen to earn their lowest-possible revenues in the same scenario (where both demand and the gas price are low). There is thus no anti-correlation between technology revenues in the CVaR scenario and outside it, and thus no gains from diversification. This shows that the missing market that drives the results in the previous sections is the absence of risk trading between investors and consumers (rather than between investors). However, this is dependent on the experimental setup. A comprehensive comparison of the investor formulations is beyond our scope. However, we report that if we only include uncertainty in the gas price, the use of a representative investor formulation in the "risk-averse & missing markets" case leads to more investment in renewables as a hedge against the high gas price scenario. This leads to emissions of 11.2 Mt, lower than the emissions from model (8), equal to 13.2 Mt (as shown in Figure S1 in the supplementary document). Importantly, these emissions are equal to the corresponding emissions in the complete market case (11.2 Mt), and lower than in the risk-neutral case (13.0 Mt). Therefore, this result constitutes an exception to our main finding that incomplete markets imply higher emissions. This leads us to ask how much demand uncertainty would be necessary to drive an increase in emissions in the missing markets case with a representative investor agent. We test a case with both demand and gas price uncertainty, where demand only varies by 5% (instead of our main assumption of 25%). The results show that emissions increase in the missing markets case relative to complete markets and risk neutrality. This suggests that even a small amount of demand uncertainty is sufficient for our main finding to hold in our illustrative case study.

In the Supplementary Materials, we also test the sensitivity of our results to alternative risk aversion parameters, price caps, and to the use of full-year data with 8760 time steps. These tests do not alter our findings regarding the impacts of missing markets on emissions and clean energy investments.

4. Conclusions

This paper shows that the incompleteness of long-term markets may distort power system investments away from variable renewables and storage, and consequently increase power system emissions. In exploratory experiments comparing a power system with missing long-term markets to an optimal system, where markets are complete, we observe less investment in variable renewables and storage when risk markets are missing. We also observe that emissions are higher in the absence of long-term markets, which is driven by the lower renewable capacities in this case. Our analysis indicates that variable renewable investments are relatively strongly impacted by risk exposure both because of their capital intensity (i.e., how the cost of capital affects the total technology cost) and their sensitivity to cost increases (i.e., how the total cost affects investment in equilibrium). These results suggest that the missing market problem can interfere with societal climate goals. Therefore, this problem warrants further consideration from policy makers seeking to decarbonize power systems.

Several policy implications follow from our results. It is currently debated how renewable and storage technologies should recover investment costs. In U.S. markets and some European countries, renewable investors rely on PPAs. This reliance implies that investments are limited by the degree to which markets for such contracts are complete.

[18] The result was obtained for an optimality tolerance of 1e−9, relative to an optimal objective value of 13.2 and an objective coefficient range between 2e−4 and 5e−3.

The incompleteness of these markets suggests a role for new market mechanisms and policy interventions (Newbery, 2016; de Maere d'Aertrycke et al., 2017; Batlle et al., 2023). This problem is not new and has already motivated the concept of hybrid markets combining liberalized short-term markets with, possibly government-aided, long-term contracting (Abada et al., 2019; Pierpont, 2020; Joskow, 2021; Wolak, 2022; Batlle et al., 2023). What we show is that addressing the incompleteness of long-term markets could also reduce future power system emissions. This strengthens the case for hybrid markets in general and for mechanisms that reduce investors' risk exposure in particular. Such mechanisms include contracts-for-differences (CfDs) (Beiter et al., 2024), similar measures being used by U.S. states, such as New York's index renewable energy credit contracts, as well as Renewable Portfolio Standards that mandate long-term contracting. It would be important for long-term mechanisms to avoid distorting operational signals, which motivates discussions of financial CfDs (Huntington et al., 2017; Schittekatte and Batlle, 2023). Our results also lend support to policy and market design measures that help manage the risks faced by storage investors. This could include long-term contracting, the design of which was explored by Billimoria and Simshauser (2023).

We also show that risk has two important implications for policy research. First, accounting for risk can considerably change results from generation expansion modeling. We find that model results can change considerably when including investor risk aversion and market incompleteness relative to the more common use of risk-neutral stochastic optimization. We note however that stochastic optimization can incorporate risk exogenously through technologies' discount rates. Future research could compare this exogenous approach to ours. Second, generation expansion modeling facilitates a better understanding of how risk impacts investment by capturing key systemic interactions. Specifically, we demonstrate how the impact of risk on investment depends not only on technologies' capital intensities but also, first, on their endogenous risk premia and, second, on how sensitive technology investments are to changes in their total cost, which is determined by technologies' system values.

Further research is required to understand the extent to which these findings generalize to real-world power systems. Though we find our conclusions hold across key sensitivities, our numerical results are not meant to anticipate actual market outcomes. A limitation of this paper is that, even though we endogenize risk, our representation of it is simplified compared to the complexity of real-world risk markets. Our main model assumes an absence of risk trading, even though investors are able to hedge some risk through different power market contracts as well as other securities traded on broader risk markets (Mays et al., 2019; de Maere d'Aertrycke et al., 2017). Accounting for partial risk trading would bring our "risk-averse & missing markets" results closer to the "risk-averse & complete markets" case. This may change the direction in which emissions change from the risk-neutral case to the "risk-averse & missing markets" case. A further numerical limitation is our use of a limited set of technologies and scenarios. Future work could perform more detailed numerical experiments, include long-duration storage, and model policy solutions to the missing market problem. This paper also omits renewable volume risk stemming from inter-annual meteorological variability. Accounting for this would require more detailed financial modeling that captures renewable variability throughout the lifetime of asset which is beyond our scope. Future research could also explore the role of policy uncertainty. Though this is not the focus of this paper, the stochasticity in the gas price that we model can be equivalently interpreted as variability in a carbon price.

Data and code availability

Our equilibrium model (8) and the data used are publicly available at: https://doi.org/10.5281/zenodo.10709502

Table A.8
Technology capacities (GW) by risk representation and source of risk RN: Risk-neutral; RA: Risk-averse; MM: Missing markets; CM: Complete markets.

Resource	Risk case	Main results (demand and gas price stochasticity)	Only demand stochasticity	Only gas price stochasticity
	RN	20.5	20.5	15.4
Gas	RA & MM	22.5	21.4	15.4
	RA & CM	19.3	19.8	15.2
	RN	26.5	26.5	25.7
Wind	RA & MM	22.8	23.8	25.9
	RA & CM	31.7	31.2	25.6
	RN	14.8	14.8	15.4
Solar	RA & MM	11.2	14.3	14.7
	RA & CM	18.2	15.4	19.6
	RN	3.1	3.1	2.8
Battery	RA & MM	1.1	2.3	2.8
	RA & CM	3.5	3.2	2.9

CRediT authorship contribution statement

Emil Dimanchev: Conceptualization, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Steven A. Gabriel:** Investigation, Methodology, Validation, Writing – review & editing. **Lina Reichenberg:** Validation, Writing – review & editing. **Magnus Korpås:** Funding acquisition, Supervision, Validation, Writing – review & editing.

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 and code availability

Our equilibrium model (8) and the data used are publicly available at: https://zenodo.org/records/10709502.

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Appendix A. Additional results

See Table A.8.

Appendix B. Representative investor formulation

While our main investor formulation (3) includes one technology r per investor agent, we propose an alternative that uses a "representative investor" agent. The key difference here is that the representative investor can invest in all technologies r. This investor solves the following linear optimization problem. This problem is easily incorporated into our equilibrium model (8) by deriving the primal–dual formulation of (B.1) and following the same reformulation steps we showed above.

$$\max_{\alpha^{inv}} \ \Omega\left[\sum_s \sum_f P_{sf} \sum_r \left[\pi_{rsf} x_r - C_r^{inv} x_r\right]\right]$$

$$+ (1-\Omega)\left[\tilde{\zeta} - \frac{1}{\Psi}\sum_s \sum_f P_{sf}\tilde{u}_{sf}\right] \tag{B.1a}$$

$$\text{s.t.} \quad x_r \geq 0 \quad \forall\, r \in R \tag{B.1b}$$

$$\tilde{u}_{sf} \geq \tilde{\zeta} - \sum_r \pi_{rsf} x_r + \sum_r C_r^{inv} x_r \quad \forall\, s \in S, f \in F\ (\tilde{\theta}_{sf}) \tag{B.1c}$$

$$\tilde{u}_{sf} \geq 0 \quad \forall\, s \in S, f \in F \tag{B.1d}$$

$$\tilde{\zeta} \in \mathbb{R} \tag{B.1e}$$

Appendix C. Karush–Kuhn–Tucker conditions of the main optimization problems

The KKT conditions of the investor optimization problem (3) follow. Note that in the derivation of these KKT conditions, $1-\Omega$ was multiplied by both sides of constraint (3c). These conditions are necessary and sufficient since (3) is a linear program.

$$0 \leq x_r \perp C_r^{inv} - \sum_s \sum_f (\Omega P_{sf} + (1-\Omega)\theta_{rsf})\pi_{rsf} \geq 0 \quad \forall\, r \in R \tag{C.1a}$$

$$0 \leq u_{rsf} \perp \frac{1}{\Psi} P_{sf} - \theta_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{C.1b}$$

$$\zeta_r \in \mathbb{R}\ ;\ \sum_s \sum_f \theta_{rsf} = 1 \quad \forall\, r \in R \tag{C.1c}$$

$$0 \leq \theta_{rsf} \perp u_{rsf} - (\zeta_r - \pi_{rsf} x_r + C_r^{inv} x_r) \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{C.1d}$$

The KKT conditions of the system operator's optimization problem (2) follow. These conditions are necessary and sufficient since (2) is linear.

$$0 \leq g_{rtsf} \perp W_t C_{rf}^{var} - \lambda_{tsf} + \mu_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{C.2a}$$

$$0 \leq y_{tsf} \perp W_t C^{cap} - \lambda_{tsf} \geq 0 \quad \forall\, t \in T, s \in S, f \in F \tag{C.2b}$$

$$0 \leq e_{rtsf} \perp \phi_{rtsf}^{soc} - \phi_{rt+1sf}^{soc} + \phi_{rtsf}^{cap} - \xi_{rt+1sf}^{d} \geq 0$$
$$\forall\, r \in O, t \in \{1,2,\ldots,|T|-1\}, s \in S, f \in F \tag{C.2c}$$

$$0 \leq e_{r|T|sf} \perp \phi_{r|T|sf}^{soc} - \phi_{r1sf}^{soc} + \phi_{r|T|sf}^{cap} - \xi_{r1sf}^{d} \geq 0 \quad \forall\, r \in O, s \in S, f \in F \tag{C.2d}$$

$$0 \leq z_{rtsf}^{ch} \perp -F^{ch}\phi_{rtsf}^{soc} + \phi_{rtsf}^{c} + \phi_{rtsf}^{bal} + \lambda_{tsf} \geq 0$$
$$\forall\, r \in O, t \in T, s \in S, f \in F \tag{C.2e}$$

$$0 \leq z_{rtsf}^{dch} \perp \frac{1}{F^{dch}}\phi_{rtsf}^{soc} + \phi_{rtsf}^{d} + \xi_{rtsf}^{d} + \phi_{rtsf}^{bal} - \lambda_{tsf} \geq 0$$
$$\forall\, r \in O, t \in T, s \in S, f \in F \tag{C.2f}$$

$$\lambda_{tsf} \in \mathbb{R}\ ;\ D_{ts} - \left(\sum_r^{|G|} g_{rtsf} + \sum_r^{|O|}\left[z_{rtsf}^{dch} - z_{rtsf}^{ch}\right] + y_{tsf}\right) = 0$$
$$\forall\, t \in T, s \in S, f \in F \tag{C.2g}$$

$$0 \leq \mu_{rtsf} \perp x_r A_{rt} - g_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{C.2h}$$

$$\phi_{r1sf}^{soc} \in \mathbb{R}\ ;\ e_{r1sf} - (e_{r|T|sf} - \frac{1}{F^{dch}} z_{r1sf}^{dch} + F^{ch} z_{r1sf}^{ch}) = 0$$
$$\forall\, r \in O, s \in S, f \in F \tag{C.2i}$$

$$\phi_{rtsf}^{soc} \in \mathbb{R}\ ;\ e_{rtsf} - (e_{rt-1sf} - \frac{1}{F^{dch}} z_{rtsf}^{dch} + F^{ch} z_{rtsf}^{ch}) = 0$$
$$\forall\, r \in O, t \in \{2,3,\ldots|T|\}, s \in S, f \in F \tag{C.2j}$$

$$0 \leq \phi_{rtsf}^{cap} \perp \frac{1}{N_r^s} x_r - e_{rtsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{C.2k}$$

$$0 \leq \phi_{rtsf}^{c} \perp x_r - z_{rtsf}^{ch} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{C.2l}$$

$$0 \leq \phi_{rtsf}^{d} \perp x_r - z_{rtsf}^{dch} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{C.2m}$$

$$0 \leq \xi_{r1sf}^{d} \perp e_{r|T|sf} - z_{r1sf}^{dch} \geq 0 \quad \forall\, r \in O, s \in S, f \in F \tag{C.2n}$$

$$0 \leq \xi_{rtsf}^{d} \perp e_{rt-1sf} - z_{rtsf}^{dch} \geq 0 \quad \forall\, r \in O, t \in \{2,3,\ldots,|T|\}, s \in S, f \in F \tag{C.2o}$$

$$0 \leq \phi_{rtsf}^{bal} \perp x_r - (z_{rtsf}^{dch} + z_{rtsf}^{ch}) \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{C.2p}$$

Appendix D. Numerical information

To solve model (8), we define upper bounds for capacity x_r. We do this heuristically based on the characteristics of the modeled system. For the gas plant investor, there is no incentive to install more capacity than the system's peak demand. For renewable capacities, since they can exceed peak demand, we set the upper bounds to be 50% larger than peak demand. For batteries, we assume capacity will not exceed 25% of peak demand. Both the storage and renewable bounds are informed by prior work modeling capacity mixes in low-carbon power systems across a large range of scenarios (Sepulveda et al., 2018). In sensitivity testing, relaxing these bounds increased solution times but did not change our results.

Our main instance of model (8) contains 49,032 continuous variables, 16 quadratic constraints, and 16 binary variables. We solved the model using the Gurobi solver v11.0.0 on a cluster with 48-core Intel(R) Xeon(R) 2.10 GHz CPUs and 32 GB RAM. The main case featuring risk aversion, missing markets, and four scenarios solves in approximately 1000 s. The same case solves in 350 s when using the "representative investor" formulation (resulting in the same solution), showcasing that this approach offers a computational advantage. The model instance only including demand uncertainty (thus containing two scenarios instead of four) solves in 131 s, which when compared to the 1000 s main case solution time showcases the large computational burden from the number of scenarios. The test including the baseload technology (for a total of five technologies) and four scenarios solves in approximately 6400 s with the main formulation and 600 s with the representative investor version. A full-year version with 8760 time steps solves in approximately 44,000 s using the representative investor formulation.

Appendix E. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107639.

References

Abada, I., De Maere D'Aertrycke, G., Ehrenmann, A., Smeers, Y., 2019. What models tell us about long-term contracts in times of the energy transition. Econ. Energy Environ. Policy 8, 163–182, Publisher: International Association for Energy Economics..

Batlle, C., Schittekatte, T., Mastropietro, P., Rodilla, P., 2023. The EU commission's proposal for improving the electricity market design: Treading water, but not drowning. Curr. Sustain./Renew. Energy Rep. http://dx.doi.org/10.1007/s40518-023-00223-4.

Beiter, P., Guillet, J., Jansen, M., Wilson, E., Kitzing, L., 2024. The enduring role of contracts for difference in risk management and market creation for renewables. Nat. Energy 9, 20–26. http://dx.doi.org/10.1038/s41560-023-01401-w, number: 1 Publisher: Nature Publishing Group..

Bichuch, M., Hobbs, B.F., Song, X., 2023. Identifying optimal capacity expansion and differentiated capacity payments under risk aversion and market power: A financial Stackelberg game approach. Energy Econ. 120, 106567. http://dx.doi.org/10.1016/j.eneco.2023.106567.

Billimoria, F., Fele, F., Savelli, I., Morstyn, T., McCulloch, M., 2022. An insurance mechanism for electricity reliability differentiation under deep decarbonization. Appl. Energy 321, 119356. http://dx.doi.org/10.1016/j.apenergy.2022.119356.

Billimoria, F., Simshauser, P., 2023. Contract design for storage in hybrid electricity markets. Joule 7, 1663–1674. http://dx.doi.org/10.1016/j.joule.2023.07.002, publisher: Elsevier..

de Maere d'Aertrycke, G., Ehrenmann, A., Smeers, Y., 2017. Investment with incomplete markets for risk: The need for long-term contracts. Energy Policy 105, 571–583. http://dx.doi.org/10.1016/j.enpol.2017.01.029.

DeCarolis, J.F., 2011. Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. Energy Econ. 33, 145–152. http://dx.doi.org/10.1016/j.eneco.2010.05.002.

Diaz, G., Inzunza, A., Moreno, R., 2019. The importance of time resolution, operational flexibility and risk aversion in quantifying the value of energy storage in long-term energy planning studies. Renew. Sustain. Energy Rev. 112, 797–812. http://dx.doi.org/10.1016/j.rser.2019.06.002.

Dimanchev, E.G., Hodge, J.L., Parsons, J.E., 2021. The role of hydropower reservoirs in deep decarbonization policy. Energy Policy 155, 112369. http://dx.doi.org/10.1016/j.enpol.2021.112369.

Dukan, M., Kitzing, L., 2023. A bigger bang for the buck: The impact of risk reduction on renewable energy support payments in Europe. Energy Policy 173, 113395. http://dx.doi.org/10.1016/j.enpol.2022.113395.

Ehrenmann, A., Smeers, Y., 2011. Generation capacity expansion in a risky environment: A stochastic equilibrium analysis. Oper. Res. 59, 1332–1346. http://dx.doi.org/10.1287/opre.1110.0992.

EIA, 2022a. Annual Energy Outlook 2022. Technical Report, Energy Information Administration. Washington, DC., URL https://www.eia.gov/outlooks/aeo/IIF_pipeline/index.php.

EIA, 2022b. U.S. electricity profile 2021. URL https://www.eia.gov/electricity/state/index.php.

Fortuny-Amat, J., McCarl, B., 1981. A representation and economic interpretation of a two-level programming problem. J. Oper. Res. Soc. 32, 783–792, URL https://www.jstor.org/stable/2581394. publisher: Palgrave Macmillan Journals.

Gabriel, S.A., Conejo, A.J., Fuller, J.D., Hobbs, B.F., Ruiz, C., 2013. Complementarity Modeling in Energy Markets. In: International Series in Operations Research & Management Science, vol. 180, New York, NY, http://dx.doi.org/10.1007/978-1-4419-6123-5.

Gabriel, S.A., García-Bertrand, R., Sahakij, P., Conejo, A.J., 2006. A practical approach to approximate bilinear functions in mathematical programming problems by using Schur's decomposition and SOS type 2 variables. J. Oper. Res. Soc. 57, 995–1004. http://dx.doi.org/10.1057/palgrave.jors.2602052.

Gérard, H., Leclère, V., Philpott, A., 2018. On risk averse competitive equilibrium. Oper. Res. Lett. 46, 19–26. http://dx.doi.org/10.1016/j.orl.2017.10.011.

Grubb, M., Newbery, D., 2018. UK electricity market reform and the energy transition: Emerging lessons. Energy J. 39, http://dx.doi.org/10.5547/01956574.39.6.mgru.

Gurobi, 2020. Non-Convex Quadratic Optimization. URL https://www.gurobi.com/events/non-convex-quadratic-optimization/.

Hoschle, H., Le Cadre, H., Smeers, Y., Papavasiliou, A., Belmans, R., 2018. An ADMM-based method for computing risk-averse equilibrium in capacity markets. IEEE Trans. Power Syst. 33, 4819–4830. http://dx.doi.org/10.1109/TPWRS.2018.2807738.

Hu, M.C., Hobbs, B.F., 2010. Analysis of multi-pollutant policies for the U.S. power sector under technology and policy uncertainty using MARKAL. Energy 35, 5430–5442. http://dx.doi.org/10.1016/j.energy.2010.07.001.

Huntington, S.C., Rodilla, P., Herrero, I., Batlle, C., 2017. Revisiting support policies for RES-E adulthood: Towards market compatible schemes. Energy Policy 104, 474–483. http://dx.doi.org/10.1016/j.enpol.2017.01.006.

Joskow, P.L., 2021. From hierarchies to markets and partially back again in electricity: responding to decarbonization and security of supply goals. J. Inst. Econ. 1–17. http://dx.doi.org/10.1017/S1744137421000400.

Keppler, J.H., Quemin, S., Saguan, M., 2022. Why the sustainable provision of low-carbon electricity needs hybrid markets. Energy Policy 171, 113273. http://dx.doi.org/10.1016/j.enpol.2022.113273.

Larson, E., Greig, C., Jenkins, J., Mayfield, E., Pascale, A., Zhang, C., Drossman, J., Williams, R., Pacala, S., Socolow, R., Baik, E.J., Birdsey, R., Duke, R., Jones, R., Haley, B., Leslie, E., Paustian, K., Swan, A., 2020. Net-Zero America: Potential Pathways, Infrastructure, and Impacts. Report, Princeton University, URL https://netzeroamerica.princeton.edu/the-report.

Leibowicz, B.D., 2018. The cost of policy uncertainty in electric sector capacity planning: Implications for instrument choice. Electr. J. 31, 33–41. http://dx.doi.org/10.1016/j.tej.2017.12.001.

Mallapragada, D.S., Sepulveda, N.A., Jenkins, J.D., 2020. Long-run system value of battery energy storage in future grids with increasing wind and solar generation. Appl. Energy 275, http://dx.doi.org/10.1016/j.apenergy.2020.115390, publisher: Elsevier Ltd..

Markowitz, H., 1952. Portfolio selection. J. Finance 7, 77–91. http://dx.doi.org/10.1111/j.1540-6261.1952.tb01525.x.

Mays, J., Craig, M.T., Kiesling, L., Macey, J.C., Shaffer, B., Shu, H., 2022. Private risk and social resilience in liberalized electricity markets. Joule 6, 369–380. http://dx.doi.org/10.1016/j.joule.2022.01.004.

Mays, J., Jenkins, J.D., 2023. Financial risk and resource adequacy in markets with high renewable penetration. IEEE Trans. Energy Mark. Policy Regul. 1–13. http://dx.doi.org/10.1109/TEMPR.2023.3322531.

Mays, J., Morton, D.P., O'Neill, R.P., 2019. Asymmetric risk and fuel neutrality in electricity capacity markets. Nat. Energy 4, 948–956. http://dx.doi.org/10.1038/s41560-019-0476-1.

Meunier, G., 2013. Risk aversion and technology mix in an electricity market. Energy Econ. 40, 866–874. http://dx.doi.org/10.1016/j.eneco.2013.10.010.

MIT Energy Initiative and Princeton University ZERO lab, 2023. GenX: a configurable power system capacity expansion model for studying low-carbon energy futures. URL https://github.com/GenXProject/GenX.

Möbius, T., Riepin, I., Müsgens, F., van der Weijde, A.H., 2023. Risk aversion and flexibility options in electricity markets. Energy Econ. 106767. http://dx.doi.org/10.1016/j.eneco.2023.106767.

Munoz, F.D., van der Weijde, A.H., Hobbs, B.F., Watson, J.P., 2017. Does risk aversion affect transmission and generation planning? A Western North America case study. Energy Econ. 64, 213–225. http://dx.doi.org/10.1016/j.eneco.2017.03.025.

Neuhoff, K., De Vries, L., 2004. Insufficient incentives for investment in electricity generations. Util. Policy 12, 253–267. http://dx.doi.org/10.1016/j.jup.2004.06.002.

Neuhoff, K., May, N., Richstein, J.C., 2022. Financing renewables in the age of falling technology costs. Resour. Energy Econ. 70, 101330. http://dx.doi.org/10.1016/j.reseneeco.2022.101330.

Newbery, D., 2016. Missing money and missing markets: Reliability, capacity auctions and interconnectors. Energy Policy 94, 401–410. http://dx.doi.org/10.1016/j.enpol.2015.10.028.

NREL, 2022. 2022 Annual Technology Baseline. Technical Report, National Renewable Energy Laboratory, Golden, CO, URL https://atb.nrel.gov/.

Pierpont, B., 2020. A Market Mechanism for Long-Term Energy Contracts To Support Electricity System Decarbonization. Technical Report, World Resources Institute.

Pineda, S., Boomsma, T.K., Wogrin, S., 2018. Renewable generation expansion under different support schemes: A stochastic equilibrium approach. European J. Oper. Res. 266, 1086–1099. http://dx.doi.org/10.1016/j.ejor.2017.10.027.

Polzin, F., Egli, F., Steffen, B., Schmidt, T.S., 2019. How do policies mobilize private finance for renewable energy?—A systematic review with an investor perspective. Appl. Energy 236, 1249–1268. http://dx.doi.org/10.1016/j.apenergy.2018.11.098.

Radner, R., 1970. Problems in the Theory of Markets under Uncertainty. Am. Econ. Rev. 60, 454–460.

Reichenberg, L., Siddiqui, A.S., Wogrin, S., 2018. Policy implications of downscaling the time dimension in power system planning models to represent variability in renewable output. Energy 159, 870–877. http://dx.doi.org/10.1016/j.energy.2018.06.160.

RGGI Inc., 2023. Allowance Prices and Volumes. URL https://www.rggi.org/auctions/auction-results/prices-volumes.

Roald, L.A., Pozo, D., Papavasiliou, A., Molzahn, D.K., Kazempour, J., Conejo, A., 2023. Power systems optimization under uncertainty: A review of methods and applications. Electr. Power Syst. Res. 214, 108725. http://dx.doi.org/10.1016/j.epsr.2022.108725.

Rockafellar, R.T., Uryasev, S., 2002. Conditional value-at-risk for general loss distributions. J. Bank. Financ. 26, 1443–1471. http://dx.doi.org/10.1016/S0378-4266(02)00271-6.

Ruiz, C., Conejo, A.J., Smeers, Y., 2012. Equilibria in an oligopolistic electricity pool with stepwise offer curves. IEEE Trans. Power Syst. 27, 752–761. http://dx.doi.org/10.1109/TPWRS.2011.2170439, conference Name: IEEE Transactions on Power Systems..

Schittekatte, T., Batlle, C., 2023. Power Price Crisis in the EU 3.0: Proposals to Complete Long-Term Markets -. URL https://ceepr.mit.edu/workingpaper/power-price-crisis-in-the-eu-3-0-proposals-to-complete-long-term-markets/.

Scott, I.J., Carvalho, P.M.S., Botterud, A., Silva, C.A., 2021. Long-term uncertainties in generation expansion planning: Implications for electricity market modelling and policy. Energy 227, 120371. http://dx.doi.org/10.1016/j.energy.2021.120371.

Sepulveda, N.A., Jenkins, J.D., de Sisternes, F.J., Lester, R.K., 2018. The role of firm low-carbon electricity resources in deep decarbonization of power generation. Joule 1–18. http://dx.doi.org/10.1016/j.joule.2018.08.006.

Sherwin, E.D., Henrion, M., Azevedo, I.M.L., 2018. Estimation of the year-on-year volatility and the unpredictability of the United States energy system. Nat. Energy 3, 341–346. http://dx.doi.org/10.1038/s41560-018-0121-4.

Siddiqui, S., Gabriel, S.A., 2013. An SOS1-based approach for solving MPECs with a natural gas market application. Netw. Spat. Econ. 13, 205–227. http://dx.doi.org/10.1007/s11067-012-9178-y.

Staum, J., 2007. Chapter 12 incomplete markets. In: Birge, J.R., Linetsky, V. (Eds.), HAndbooks in Operations Research and Management Science. In: Financial Engineering, volume 15, Elsevier, pp. 511–563. http://dx.doi.org/10.1016/S0927-0507(07)15012-X.

Stiglitz, J.E., 1982. The inefficiency of the stock market equilibrium. Rev. Econ. Stud. 49, 241–261. http://dx.doi.org/10.2307/2297273.

Tanaka, M., Conejo, A.J., Siddiqui, A.S., 2022. Environmental Externalities, Economics of Power Systems. In: International Series in Operations Research & Management Science, Springer International Publishing, Cham, pp. 197–254.

Tietjen, O., Pahle, M., Fuss, S., 2016. Investment risks in power generation: A comparison of fossil fuel and renewable energy dominated markets. Energy Econ. 58, 174–185. http://dx.doi.org/10.1016/j.eneco.2016.07.005.

Wogrin, S., Barquín, J., Centeno, E., 2013. Capacity expansion equilibria in liberalized electricity markets: An EPEC approach. IEEE Trans. Power Syst. 28, 1531–1539. http://dx.doi.org/10.1109/TPWRS.2012.2217510, conference Name: IEEE Transactions on Power Systems.

Wolak, F.A., 2022. Long-term resource adequacy in wholesale electricity markets with significant intermittent renewables. Environ. Energy Policy Econ. 3, 155–220. http://dx.doi.org/10.1086/717221, publisher: The University of Chicago Press..

Yang, J., Fuss, S., Johansson, D.J.A., Azar, C., 2023. Investment dynamics in the energy sector under carbon price uncertainty and risk aversion. Energy Clim. Change 4, 100110. http://dx.doi.org/10.1016/j.egycc.2023.100110.