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# Consequences of the missing risk market problem for power system emissions

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## Abstract

Financial risk is a central concern for investors in electricity technologies. Investors are both risk-averse and unable to optimally manage risk due to the incompleteness of financial markets. This missing market problem may have important consequences for climate policy goals. However, research often omits this problem by assuming investors to be risk-neutral. Here, we develop a new model of risk-averse generation expansion with missing markets. Our approach reformulates the problem to facilitate solutions via integer programming, which enables us to address the multiple equilibrium property inherent to such models. We solve our model for a stylized power system featuring gas, wind, solar, and batteries under demand and gas price uncertainty. We find that emissions are higher if investors are risk-averse and markets for risk are missing, than if investors are assumed to be risk-neutral. Our results show that the missing market problem skews the investment mix away from wind, solar, and batteries and toward gas. These effects are even larger relative to optimal risk-averse planning with complete markets. The impacts of risk depend only partly on technologies' capital intensities and are largely driven by how technologies interact at the systems level. Overall, our findings strengthen the case for policy measures that enable investors to efficiently manage risk.

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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)

$\Omega$ Weight for risk aversion (fraction)

$\Psi$ Probability level used to parameterize risk aversion (fraction)

$A_{rt}$ Availability of generation resource (fraction)

$C^{inv}_{r}$ Investment cost (\$/MW)

$F^{ch}$ Charging efficiency (fraction)

$F^{dch}$ Discharging efficiency (fraction)

$N^{s}_{r}$ Power to energy ratio for storage technologies (fraction)

$C^{cap}$ Price cap (\$/MWh)

$W_t$ Weight of representative time period (fraction)

$P_{sf}$ Probability of demand $s$ and gas price $f$ (fraction)

$E_r^{co2}$ 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)

$z_{rtsf}^{ch}$ Charging of storage technology (MWh)

$z_{rtsf}^{dch}$ Discharging from storage technology (MWh)

$\zeta^{cp}$ Value-at-Risk (VaR) for central planner ($)

$u_{sf}^{cp}$ Additional cost relative to VaR for central planner ($)

$\zeta_r$ 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 ($)

$\pi_{rsf}$ Revenues net of operating costs ($/MW)

**Key dual variables**

$\lambda_{tsf}$ Price of electricity ($/MWh)

$\mu_{rtsf}$ Generation capacity rent ($/MW)

$\phi_{rtsf}^{soc}, \phi_{rtsf}^{cap}, \phi_{rtsf}^{c}, \phi_{rtsf}^{d}, \phi_{rtsf}^{bal}, \xi_{rtsf}^{d}$ Dual variables corresponding to storage constraints

$\theta_{rsf}$ Risk-adjusted probability (fraction)

$\tilde{\theta}_{sf}$ Risk-adjusted probability for investor in all technologies (fraction)

# 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 using financial markets. 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. Unexpected changes in policy and other uncertainties can also affect investment. For tractability, we focus 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.

Risk refers to variance in an investment's payoff. Exposure to risk depends both on the risk investors face and on their ability to manage it. Investors manage risk by trading financial contracts that diversify the risk from a given investment. In theory, financial markets feature a complete set of financial instruments (known as Arrow-Debreu securities) that can insure investors against any possible realization of the future. This is commonly assumed in studies modeling risk-averse generation expansion (Munoz et al., 2017; Diaz et al., 2019; Möbius et al., 2023). However, it is well established that financial markets fall short of this ideal (Radner, 1970; Stiglitz, 1982; Staum, 2007). In power systems, an important hedging strategy is the use of forward contracts between investors and consumers, an example being the use of Power Purchase Agreements (PPAs). PPAs replace a variable stream of revenues with a stable return based on a pre-negotiated price and 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; 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). The purpose of this paper is to assess the implications of the missing market problem for climate goals in particular. Our experiment focuses on missing risk trading between investors and consumers, though our model is more general.

Previous work suggested that market incompleteness would 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 risk-averse generation expansion. However a large strand of this literature did not model variable renewables or storage (Ehrenmann and Smeers, 2011; Meunier, 2013; de Maere d'Aertrycke et al., 2017; Bichuch et al., 2023). Recent studies included renewable generation but omitted renewable investments (Pineda et al., 2018; Hoschle et al., 2018; Billimoria et al., 2022). Mays et al. (2019) modeled wind investment and found it decreases with missing 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-hour 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 generation expansion with missing risk markets presents challenges due to the non-convex nature of the 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 a stylized power system case study featuring both variable renewable and storage.

This paper's first contribution is a new approach to modeling generation expansion with missing markets. We follow the commonly used approach to model investors' risk exposure (Ehrenmann and Smeers, 2011; Mays et al., 2019), but reformulate the problem to facilitate numerical solutions for a problem featuring both variable renewables and storage. Another advantage of our method is that it allows us to introduce a numerical robustness procedure, analogous to modeling to generate alternatives (DeCarolis, 2011), to test for the possibility of multiple equilibria.

This work's second contribution is an analysis of how investment risk impacts the capacity mix and emissions of a power system with variable renewables, storage, and a traditional thermal technology. We disentangle 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 show that the risks investors face in the absence of risk markets lead to smaller shares of wind, solar, and batteries within the capacity mix and a higher share of gas, than if investors are assumed, as is common, to be risk-neutral. Consequently, we find that the missing market problem results in higher future emissions compared to what would be indicated by risk-neutral modeling. These effects have the same direction but an even larger magnitude if we compare the missing markets outcome to optimal risk-averse planning where markets are complete. Overall, this work shows that the missing market problem distorts market outcomes in a way that interferes with climate policy goals.

# 2 Methods

## 2.1 Introduction to 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[1]. 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

[1] Uncertainty is represented by a discrete probability distribution. Our numerical approach makes the additional assumption that this distribution is uniform.

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).

Investors' risk aversion is modeled using the Conditional Value-at-Risk (CVaR) function. In this formulation, investors weight downside scenarios[2] 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).

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 $f \in F$.

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

$$
\begin{aligned}
\min_{\alpha} \quad & \sum_{r} C_r^{inv} x_r \\
& + \Omega \Big[ \sum_{s} \sum_{f} P_{sf} \sum_{t} W_t \sum_{r} C_{rf}^{var} g_{rtsf} + \sum_{s} \sum_{f} P_{sf} \sum_{t} W_t C^{cap} y_{tsf} \Big] \\
& + (1 - \Omega) \Big[ \zeta^{cp} + \frac{1}{\Psi} \sum_{s} \sum_{f} P_{sf} u_{sf}^{cp} \Big] && \text{(1a)} \\
\text{s.t.} \quad & x_r \geq 0 \quad \forall\, r \in R && \text{(1b)} \\
& g_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F && \text{(1c)} \\
& e_{rtsf}, z_{rtsf}^{ch}, z_{rtsf}^{dch} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F && \text{(1d)} \\
& y_{tsf} \geq 0 \quad \forall\, t \in T, s \in S && \text{(1e)} \\
& u_{sf}^{cp} \geq 0 \quad \forall\, s \in S, f \in F && \text{(1f)} \\
& \zeta^{cp} \in \mathbb{R} && \text{(1g)} \\
& u_{sf}^{cp} \geq \sum_{t} W_t \sum_{r} g_{rtsf} C_{rf}^{var} + \sum_{t} W_t C^{cap} y_{tsf} - \zeta^{cp} \quad \forall\, s \in S, f \in F \qquad (\tilde{\theta}_{sf}) && \text{(1h)} \\
& \sum_{r}^{|G|} g_{rtsf} + \sum_{r}^{|O|} \left[ z_{rtsf}^{dch} - z_{rtsf}^{ch} \right] + y_{tsf} = D_{ts} \quad \forall\, t \in T, s \in S, f \in F \qquad (\lambda_{tsf}) && \text{(1i)} \\
& g_{rtsf} \leq x_r A_{t,r} \quad \forall\, r \in G, t \in T, s \in S, f \in F \qquad (\mu_{rtsf}) && \text{(1j)} \\
& e_{r1sf} = e_{r|T|sf} - \frac{1}{F^{dch}} z_{r1sf}^{dch} + F^{ch} z_{r1sf}^{ch} \quad \forall\, r \in O, s \in S, f \in F \qquad (\phi_{r1sf}^{soc}) && \text{(1k)} \\
& e_{rtsf} = e_{r,t-1,s,f} - \frac{1}{F^{dch}} z_{rtsf}^{dch} + F^{ch} z_{rtsf}^{ch} \\
& \forall\, r \in O, t \in \{2, 3, ..., |T|\}, s \in S, f \in F \qquad (\phi_{rtsf}^{soc}) && \text{(1l)} \\
& e_{rtsf} \leq \frac{1}{N_r^s} x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \qquad (\phi_{rtsf}^{cap}) && \text{(1m)} \\
& z_{rtsf}^{ch} \leq x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \qquad (\phi_{rtsf}^{c}) && \text{(1n)} \\
& z_{rtsf}^{dch} \leq x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \qquad (\phi_{rtsf}^{d}) && \text{(1o)} \\
& z_{r1sf}^{dch} \leq e_{r|T|sf} \quad \forall\, r \in O, s \in S, f \in F \qquad (\xi_{r1sf}^{d}) && \text{(1p)} \\
& z_{rtsf}^{dch} \leq e_{r,t-1,s,f} \quad \forall\, r \in O, t \in \{2, 3, ..., |T|\}, s \in S, f \in F \qquad (\xi_{rtsf}^{d}) && \text{(1q)} \\
& z_{rtsf}^{dch} + z_{rtsf}^{ch} \leq x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \qquad (\phi_{rtsf}^{bal}) && \text{(1r)}
\end{aligned}
$$

where all variables are contained in the set $\alpha = (x_r, g_{rtsf}, y_{tsf}, e_{rtsf}, z_{rtsf}^{ch}, z_{rtsf}^{dch}, \zeta^{cp}, u_{sf}^{cp})$. The objective function (1a) minimizes the total system cost, which includes: investment costs, $C_r^{inv} x_r$, and a weighted combination of expected operating costs (the first bracketed term) weighted by $\Omega$, 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 $\Psi$-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 $\Psi$ tail. The auxiliary variable $\zeta^{cp}$ takes on the value of the $\Psi$-percentile Value-at-Risk (VaR) in the optimal solution (Rockafellar and Uryasev, 2002).

Equation (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 the storage technology, following the formulation in the GenX 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 (1k)[3]. 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 distinguish between the optimization problems solved by investors and the problem solved 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 $\alpha^{iso} = (g_{rtsf}, y_{tsf}, z^{ch}_{rtsf}, z^{dch}_{rtsf}, e_{rtsf})$.

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

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

where objective function (2a) minimizes operating costs (equivalent to maximizing welfare

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

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 $\Omega$, which effectively represents the degree of risk aversion.

$$
\begin{aligned}
\max_{\alpha^{inv}} \quad & \Omega\Big[\sum_s \sum_f P_{sf}\pi_{rsf}x_r - C_r^{inv}x_r\Big] + \\
& (1-\Omega)\Big[\zeta_r - \frac{1}{\Psi}\sum_s\sum_f P_{sf}u_{rsf}\Big] && \text{(3a)}\\
\text{s.t.} \quad & x_r \geq 0 \quad \forall\, r \in R && \text{(3b)}\\
& u_{rsf} \geq \zeta_r - \pi_{rsf}x_r + C_r^{inv}x_r \quad \forall\, r \in R, s \in S, f \in F \ (\theta_{rsf}) && \text{(3c)}\\
& u_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F && \text{(3d)}\\
& \zeta_r \in \mathbb{R} \quad \forall\, r \in R && \text{(3e)}
\end{aligned}
$$

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)[4], which constrains it to the $\Psi$-worst tail of the profit distribution, as well as the auxiliary variables $\zeta_r$, which equals the $\Psi$-VaR in the optimal solution, as shown by Ehrenmann and Smeers (2011). $\pi_{rsf}$ 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 (Mays et al., 2019, e.g.). Specifically, revenues are defined as the dual $\mu_{rtsf}$ of the capacity limit constraint (1j) adjusted for the technologies availability $A_{rt}$.

[4]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.

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

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: $C_r^{inv} - \sum_s \sum_f P_{sf} \sum_t W_t(\frac{1}{N_r^s}\phi_{rtsf}^{cap} + \phi_{rtsf}^{c} + \phi_{rtsf}^{d} + \phi_{rtsf}^{bal}) \geq 0$ (this is equivalent to KKT condition (11a)). The KKT condition relates the cost a unit of capacity, $C_r^{inv}$ to its total expected value (i.e., revenues in our context). $\phi_{rtsf}^{cap}$, 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 follows:

$$\forall\, r \in O,\ \pi_{rsf} := \sum_t \left[ \frac{1}{N_r^s}\phi_{rtsf}^{cap} + \phi_{rtsf}^{c} + \phi_{rtsf}^{d} + \phi_{rtsf}^{bal} \right]$$

#### 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 market. This problem is equivalent to model (1) in a risk-neutral case, $\Omega = 1$, where risk trading is irrelevant[5].

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 non-linear programming (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 bi-linear 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 it can be solved to a global

[5]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).

optimum within a tolerance, which facilitates additional numerical tests that can address the multiple equilibrium problem inherent to such models, discussed this 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 SOS1 variables (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.

$$\sum_t W_t \sum_r C_r^{var} g_{rtsf} + \sum_t W_t C^{cap} y_t = \sum_t \lambda_{tsf} D_{ts} - \sum_r \pi_{rsf} x_r \quad \forall\, s \in S, f \in F \tag{4a}$$

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

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

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

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

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

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

$$\phi_{rtsf}^{soc} - \phi_{r,t+1,s,f}^{soc} + \phi_{rtsf}^{cap} - \xi_{r,t+1,s,f}^{d} \geq 0 \quad \forall\, r \in O, t \in \{1, 2, ..., |T|-1\}, s \in S, f \in F \tag{4h}$$

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

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

$$\frac{1}{F^{dch}} \phi_{rtsf}^{soc} + \phi_{rtsf}^{d} + \xi_{rtsf}^{d} + \phi_{rtsf}^{bal} - \lambda_{tsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{4k}$$

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

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).

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

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

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

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

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

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

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

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

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

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 $\zeta_r$, respectively. As in prior work, $\theta_{rsf}$ represents the risk-adjusted probability for scenarios in the probability distribution tail defined by parameter $\Psi$ (Ehrenmann and Smeers, 2011).

Note that problem (5) presents additional challenges for numerical solutions because of the bilinear term $\theta_{rsf}\pi_{rsf}$ in (5b), as well as the bilinear term $\pi_{rsf}x_r$ 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 hours[6]. 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 achieve is to show that, under assumptions formalized below, the continuous

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

variable $\theta_{rsf}$ 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 $S \cup F$ with $P_{sf}$ the probability of each scenario $(s, f)$ and cardinality $|S \cup F| := N^{all}$. 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; $V \subset S \cup F$, with cardinality $|V| := N^{cvar}$. Formally, $\forall\ (s, f) \in V, \pi_{rsf} x_r - C_r^{inv} x_r \leq \zeta_r$. Equivalently, $\pi_{rsf} x_r - C_r^{inv} x_r > \zeta_r\ \forall\ (s, f) \notin V$.*

Next, we explore the properties of $\theta_{rsf}$ across the different scenarios (summarized in Table 1). Recall that $\theta_{rsf}$ is the risk-adjusted probability that a risk-averse investor places on scenario $(s, f)$. As shown by Ehrenmann and Smeers (2011), $\theta_{rsf}$ 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 (11d). Further note this implies $u_{rsf} = 0$ by KKT condition (11b).*

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

Table 1: Properties of risk-adjusted probability variable $\theta_{rsf}$
These properties refer to the values of $\theta_{rsf}$ before making Assumption 1 and Assumption 2.

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 (11d), and $\theta_{rsf} = \frac{P_{sf}}{\Psi}$ by (11b). Second, if $\pi_{rsf} x_r - C_r^{inv} x_r = \zeta_r$, $u_{rsf}$ is not necessarily strictly positive, leading to: $0 \leq \theta_{rsf} \leq \frac{P_{sf}}{\Psi}$. This makes our task challenging, so, to impose stricter boundary conditions on $\theta_{rsf}$, we introduce the following assumptions.

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

**Assumption 2** $\Psi \in \{cP : c \in \{1, 2, ..., N^{all}\}\}$, *i.e., $\Psi$ 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 $\theta_{rsf}$. 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 $\Psi$ is the cumulative probability of this tail. If all scenarios have equal probability $P$, per Assumption 1, it follows that $\Psi$ is a multiple of $P$. Since $N^{cvar}$ is an integer while $\Psi$ is not necessarily an integer, $N^{cvar}P \geq \Psi$. However, if we assume that $\Psi$ is an integer multiple $P$, i.e., Assumption 2, it follows that $N^{cvar}P = \Psi$.*

Given Lemma 1, we next show that all $\theta_{rsf}$ 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 $\Psi$ with $N^{cvar}P$ in (5c). This leads to: $\theta_{rsf} \leq \frac{1}{N^{cvar}}$. Further, note that, since all $\theta_{rsf}$ sum to one by (11c), and since $\theta_{rsf}$ outside the CVaR tail are zero, by Remark 1, then the $\theta_{rsf}$ 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 $\theta_{rsf} \leq \frac{1}{N^{cvar}}$, the quality $\sum_{(s,f)\in V} \theta_{rsf} = N^{cvar}\frac{1}{N^{cvar}}$ 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 $\theta_{rsf}$, as follows:

**Proposition 2** *$\theta_{rsf} = \frac{1}{N^{cvar}}\theta^Z_{rsf} \ \forall \ (s, f) \in S \cup F$, 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, $\theta_{rsf}$ can be exactly replaced by $\frac{1}{N^{cvar}}\theta^Z_{rsf}$. As a remark, the auxiliary binary variable $\theta^Z_{rsf}$ 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).

$$
\begin{aligned}
&\theta^Z_{rsf} \in \{0,1\} \quad \forall\, r \in R, s \in S, f \in F && \text{(6a)}\\
&\frac{1}{\Psi} P_{sf} - \frac{1}{N^{cvar}} \theta^Z_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F && \text{(6b)}\\
&\sum_s \sum_f \frac{1}{N^{cvar}} \theta^Z_{rsf} = 1 \quad \forall\, r \in R && \text{(6c)}\\
&C^{inv}_r - \Omega \sum_s \sum_f P_{sf} + (1-\Omega) \sum_s \sum_f \frac{1}{N^{cvar}} \theta^Z_{rsf} \pi_{rsf} \geq 0 \quad \forall\, r \in R && \text{(6d)}
\end{aligned}
$$

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[7]. The linear expression (7f) replaces the non-convex expression (6d). The justification for this substitution is that $\nu_{rsf}$ exactly matches $\frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf}$[8].

$$
\begin{aligned}
&\nu_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F && \text{(7a)}\\
&h_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F && \text{(7b)}\\
&\nu_{rsf} \leq \bar{M} \theta^Z_{rsf} \quad \forall\, r \in R, s \in S, f \in F && \text{(7c)}\\
&h_{rsf} \leq \bar{M}(1-\theta^Z_{rsf}) \quad \forall\, r \in R, s \in S, f \in F && \text{(7d)}\\
&\nu_{rsf} + h_{rsf} = \frac{1}{N^{cvar}} \pi_{rsf} \quad \forall\, r \in R, s \in S, f \in F && \text{(7e)}\\
&C^{inv}_r - \Omega \sum_s \sum_f P_{sf} + (1-\Omega) \sum_s \sum_f \nu_{rsf} \geq 0 \quad \forall\, r \in R && \text{(7f)}
\end{aligned}
$$

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), (6), 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), (6), and (7) is algebraically equivalent to (5) under Proposition 2, which is derived from KKT conditions (11b), (11c), and (11d). These KKT conditions necessarily hold for the solution of (3), which is equivalent to the solution of (5), since (3) is a linear program.*

[7] 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).

[8] To see why note that if $\theta^z_{rsf} = 1$, then $h_{rsf} = 0$, leading to $\nu_{rsf} = \frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf}$; and if $\theta^z_{rsf} = 0$, then $\nu_{rsf} = 0 = \frac{1}{N^{cvar}}\theta^Z_{rsf}\pi_{rsf}$. 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.

The combination of the system operator's problem (4) and the new investor problem, containing (5a), (5e) - (5h), (6), 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.

$$(4), (5a), (5e) - (5h), (6), (7) \tag{8}$$

## 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 quadratic program (MIQP) 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 test

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 to global optimality. 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 MIQP.

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

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

The choice of this objective function is motivated by our main research question, which concerns the impact of risk on emissions. We are thus interested in solutions with emission outcomes that refute our main result that the missing markets problem increase emissions. Since this MIQP model can be solved 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 the risk-neutral solution, 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.

## 2.8 Experimental design

To illustrate the impact of risk on emissions, we model a stylized power system including four technologies: gas plants (combined cycle combustion), onshore wind, solar photovoltaic, and 4-hour 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 technology that 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 2, except for the investment cost of the 4-hour 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, $C_r^{inv}$, represent annualized costs, which we calculated based on the CAPEX shown in Table 2 and a risk-free discount rate of 2% (since risk is modeled endogenously). The annualized investment costs are shown in Table 4 (second column). The variable cost of gas assumes a gas price of \$3.6/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/t$CO_2$ carbon price (RGGI Inc., 2023) and a 0.4 t$CO_2$/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, $C^{cap}$, is assumed to be \$2,000/MWh, based on the New England power system (see Supplementary Material for results based on alternative values). This price cap represents in effect the model's Value of Lost Load (VOLL).

| | 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-hour) | 680 | 0 | 0 |

Table 2: Technology parameters

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 8,760 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 $\Omega = 0.5$[9] and $\Psi = 0.25$ across all models. These values are chosen for illustrative purposes. The Supplementary Material reports sensitivity tests, which do not alter our conclusions.

[9]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 address our main research question regarding the impact of the missing market problem on power system emissions, we sequentially investigate the main causal mechanisms that explain this impact. First, uncertainty results in risk exposure which differs between technologies and has a unique impact on each technology's costs (Section 3.1). Next, cost changes influence the interactions between investment decisions leading to a new equilibrium investment outcome (Section 3.2). Then, the new capacity mix impacts the operation of the power system and thus power system emissions (Section 3.3). Results are shown for three main cases featuring different representations of risk.

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

Table 3: Alternative risk cases

## 3.1 Impact of missing markets on technology costs

Here we explore each technology's risk exposure in the absence of risk markets. For this we use results from the "Risk-averse & missing markets" case (Table 3), which represents a power system with a missing market problem, and which is the focus of this paper. 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 Figure 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. 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.

Figure 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. 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).

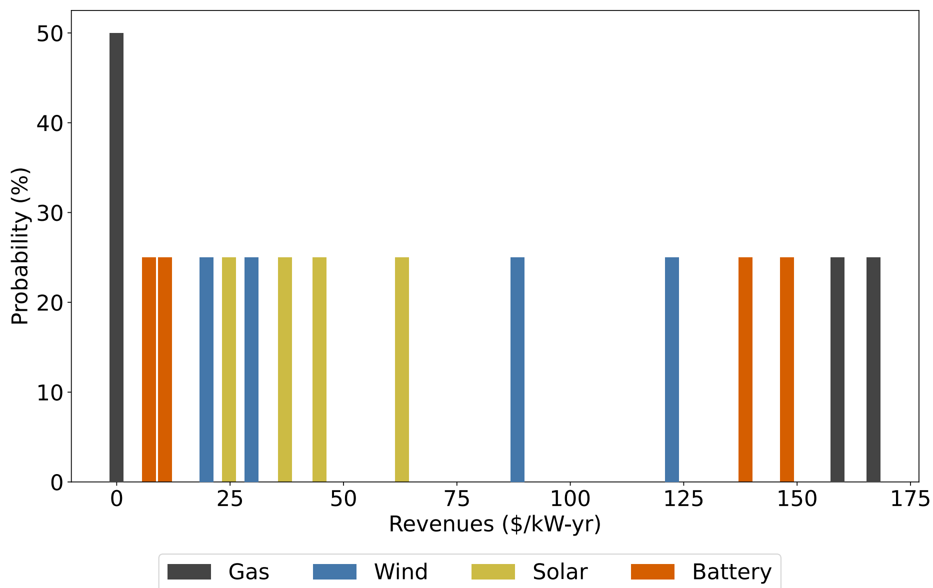


Figure 1: Probability distributions of technology revenues
Revenues represent the value of expression $\pi_{rsf}$ from the "Risk-averse & missing markets" case.

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 Figure 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)[10]. 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 column 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

[10]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.

by risk (sixth column), followed by the battery[11], wind, and solar. Wind and solar costs are less affected by risk than 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.

| | A<br>Risk-free discount rate (%) | B<br>Investment cost risk-free ($/kW-yr) | C<br>Investment cost risk-adjusted ($/kW-yr) | D<br>WACC (%) | D-A<br>Risk premium (% point) | (C-B)/B<br>Investment cost change (%) |
|---|---|---|---|---|---|---|
| Gas | 2 | 40 | 81 | 8 | 6 | 100 |
| Wind | 2 | 42 | 65 | 5 | 3 | 53 |
| Solar | 2 | 33 | 42 | 4 | 2 | 26 |
| Battery | 2 | 41 | 76 | 9 | 7 | 82 |

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

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[12] (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, i.e., from the solution of the "Risk-averse & missing markets case".

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

[11]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.

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

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.

| | 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 |

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

## 3.2 Impacts of missing markets on the capacity mix

Here we explore how risk influences the equilibrium power system capacity mix. Figure 2 shows the capacity mix resulting from different representations of risk. Our main case, "Risk-averse & missing markets" is illustrated by the second column, computed with model (8). For comparison, the first column represents a case in which market agents are risk-neutral, as is often assumed. This case is computed with model (1)[13]. The third column shows the "Risk-averse & complete markets" case, which represents the socially optimal risk-averse outcome, and is also generated with model (1).

[13]The risk-neutral case can be modeled with either the equilibrium or optimization models, but, after confirming their equivalence, we use the latter for the results.

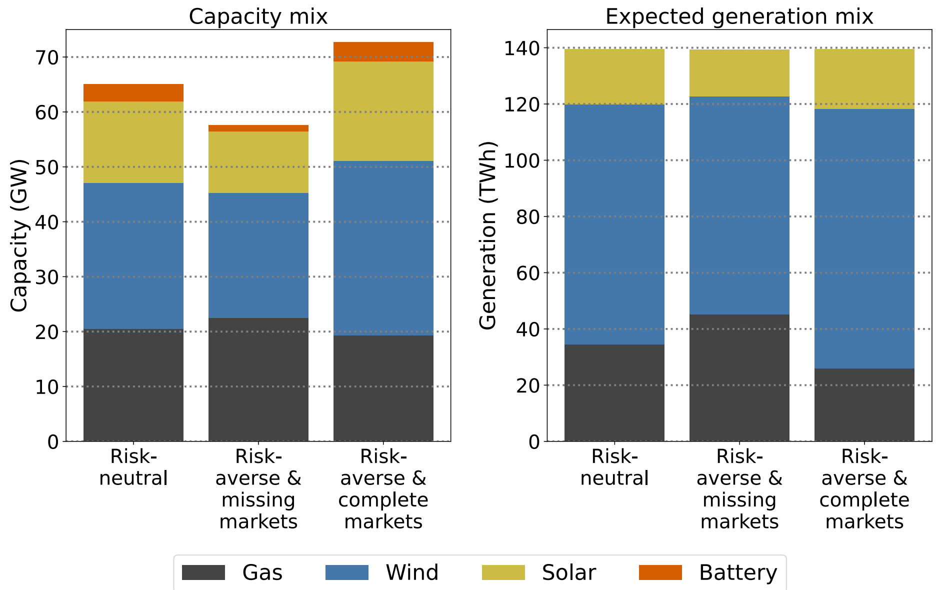


Figure 2: Capacity and generation mix for different representations of risk
All cases include both demand and gas price stochasticity. "Risk-averse & missing markets" refers to output from model (8). The remaining cases show output from (1). Generation is computed in expectation over all scenarios.

By comparing the first and second columns in Figure 2, we find the risk exposure resulting from an absence of risk markets leads to less investment in variable renewables and batteries, and more investment in gas generation, compared to the case where investors are risk-neutral. 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 overall cost. In contrast, the intermittency of wind and solar limit their system values, and make investment relatively more sensitive to a change in their overall cost.

A somewhat surprising result is that gas capacity increases in the missing markets case compared to the risk-neutral case. 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 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 nevertheless serves to illustrate that dispatchable technologies are able to capture greater value in a case of missing markets. Whether this translates to increase in gas capacity in absolute terms also depends on the degree to which competing technologies are impacted by risk, and is therefore highly case-dependent. For example, the increase in gas capacity (in absolute terms) almost disappears in our sensitivity test modeling a full year (see the Supplementary Material).

We now consider the socially optimal risk-averse outcome (third column in Figure 2). The capacity mix in this case is the result of the optimization model (1). The results represent the optimal decisions of a risk-averse central planner. Equivalently, this case reflects the socially optimal outcome in a market with risk-averse investors and risk-averse consumers[14]. This case exhibits more investment in wind, solar, and batteries and less investment in gas relative to both the missing market and risk-neutral cases. This is because, by construction, the risk-averse model 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. Previous studies showed similar results (Munoz et al., 2017; Diaz et al., 2019), though for different sets of stochastic parameters. In the context of our framework, consumers in effect pay a premium to encourage capacity investments that insure against the possibility of high operating costs. 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.

Finally, we isolate the impact of each source of risk to further understand the reason for the above 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 Tables 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 missing markets case (additional tests in the third paragraph of Section 3.6 qualify this finding in the case of gas price uncertainty). Similarly, in the complete markets case, both the demand and gas price stochasticity drive the results observed in the previous paragraph.

[14]Note that, in contrast to this complete market case, the consumers implicitly represented in the "Risk-averse & missing markets" case can be interpreted equivalently as either risk-averse or risk-neutral. This is because consumers' decisions, as represented by the system operator, lack any first-stage variables that can be influenced by risk.

### 3.3 Impacts of missing markets on power system emissions

Table 6 shows how annual power system emissions vary across alternative representations of risk. Emissions are estimated in expectation. The results show that emissions are higher in the missing markets case (second row) compared to the risk-neutral case (first row). This stems directly from the changes in the capacity mix observed earlier. As renewable capacities are lower in the the missing markets case, this leads to less renewable generation, which is replaced by gas plant generation. These changes in generation can also be observed in Figure 2. Our emissions results align with prior work using agent-based modeling (Yang et al., 2023) where the authors modeled risk-averse investment, excluding storage, under carbon price uncertainty.

In the case of complete risk markets (third row in Table 2), emissions are lower relative to the risk-neutral case. This result can be explained by the greater amount of variable renewable capacity discussed above. Comparing the case of complete markets to the case of missing markets (third and second rows) shows that the socially optimal risk-averse outcome entails lower emissions than what may result from power markets in the absence of risk trading.

We distinguish between each source of uncertainty (demand and gas prices) in Table 9 and find that the directionality of the emissions results is consistent for each source of uncertainty.

| | 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 |

Table 6: Expected $CO_2$ emissions

### 3.4 Impacts of missing markets on system cost

This section considers how investment risk impacts other key 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 perspective. The results show that system costs increase in the risk-averse case with missing markets relative to the risk-neutral case. This is driven by load shedding (i.e., non-served energy) shown in the second column, which occurs because risk-averse investors put less weight on revenues earned during load shedding, thus investing less than they otherwise would.

Turning to the case of complete risk markets, we observe that system costs are higher relative to the risk-neutral case (comparing the fourth and first rows). This outcome is by construction since the latter case is obtained from an optimization model that minimizes the expected total system cost as defined here (while in the former case the model places additional weight on costs in the most expensive scenario). In practical terms, this reflects that the risk-averse social 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.

| | 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 |

Table 7: System performance for different risk cases

### 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 8). In this case, model (9) finds a different equilibrium solution with emissions of 13.2 Mt[15], 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 risk-neutral case. 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 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. While 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

[15]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.

of \$10/MWh. The solution of the "Risk-neutral" case features capacities of: 15, 20, 7, 2 and 8 GW respectively for gas, wind, solar, batteries, and the "subsidized nuclear" technology respectively. In comparison, the "Risk-averse & missing markets" case results in capacities of: 17, 17, 6, 1, and 7 GW. Therefore, the results of this test are consistent with our capacity mix results. We further confirm this is also the case for our emissions results.

We also test the sensitivity of our results to the presence of the storage technology. We confirm that the changes in capacity and emissions between the risk 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. When modeling both demand and gas price uncertainty, we find that the two formulations result in the same solution. 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 set-up. 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 (relative to risk neutrality) 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 reported in the last column of appendix Table 9. Importantly, emissions are also 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 shows that emissions increase in the missing markets case relative to 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.

# 4 Conclusions

This paper finds that an absence of risk markets distorts power system investments away from variable renewables and storage, and consequently increases power system emissions. This finding suggests that the missing market problem interferes with climate policy objectives. Therefore, this market failure warrants attention from policy makers seeking to decarbonize power systems.

Several specific 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. The incompleteness of these markets suggests a role for policy intervention (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, which combine liberalized short-term markets and government-aided long-term contracting (Abada et al., 2019; Joskow, 2021; Batlle et al., 2023). What we show is that addressing this problem would also reduce future power system emissions. This strengthens the case for hybrid markets in general and for policies that reduce investors' risk exposure in particular. Such policies include contracts-for-differences (CfDs) and similar measures being used by U.S. states, such as New York's index renewable energy credit contracts. It must be acknowledged that such policies transfer risk to another party, for example, a taxpayer-funded agency. Such public risk burden should be weighed against the benefits of de-risking clean energy investments, which, as we show, include climate mitigation. It would also be important for such policies to avoid distorting operational signals, which motivates recent discussions of financial CfDs and their design features (Huntington et al., 2017; Schittekatte and Batlle, 2023). Our results also lend support to policy and market design measures that help mitigate 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 have important implications for 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, this work illustrates that modeling risk endogenously within a generation expansion model captures how the impact of risk on investment depends not only on technologies' capital intensities but also on their endogenous risk premia and system values.

Our numerical results are not meant to anticipate actual market outcomes but to indicate more generally how risk can interact with generation expansion and power system operation. A limitation of this work is that, even though we endogenize risk, our representation of it is simplified compared to the complexity of real-world financial markets. Our main results assume 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 financial markets (Mays et al., 2019; de Maere d'Aertrycke et al., 2017). A further numerical limitation is our use of a limited set of technologies and scenarios. Future work could perform more detailed numerical experiments and model alternative policy solutions to the missing market problem. Future work 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. This paper also omits renewable volume risk stemming from interannual meteorological variability. Accounting for these effects would require more detailed financial modeling that captures renewable variability throughout the lifetime of asset which is beyond our scope.

# Appendices

# A Additional results

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

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

| Risk case | Demand and gas price stochasticity | Demand stochasticity | Gas price stochasticity |
|---|---|---|---|
| Risk-neutral | 13.8 | 13.8 | 13.0 |
| Risk-averse & missing markets | 18.1 | 15.7 | 13.2 |
| Risk-averse & complete markets | 10.4 | 11.6 | 11.2 |

Table 9: Expected $CO_2$ emissions by risk representation and source of risk

# 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 (10) and following the same reformulation steps we showed above.

$$\max_{\alpha^{inv}} \ \Omega\Bigg[\sum_s \sum_f P_{sf} \sum_r \left[\pi_{rsf} x_r - C_r^{inv} x_r\right]\Bigg] + (1-\Omega)\Bigg[\tilde{\zeta} - \frac{1}{\Psi}\sum_s \sum_f P_{sf}\tilde{u}_{sf}\Bigg] \tag{10a}$$

$$\text{s.t.} \quad x_r \geq 0 \quad \forall\, r \in R \tag{10b}$$

$$\tilde{u}_{sf} \geq \tilde{\zeta} - \sum_r \pi_{rsf} x_r + \sum_r C_r^{inv} x_r \quad \forall\, s \in S, f \in F \ (\tilde{\theta}_{sf}) \tag{10c}$$

$$\tilde{u}_{sf} \geq 0 \quad \forall\, s \in S, f \in F \tag{10d}$$

$$\tilde{\zeta} \in \mathbb{R} \tag{10e}$$

# 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.

$$0 \leq x_r \perp C_r^{inv} - \sum_s \sum_f (\Omega P_{sf} + (1-\Omega)\theta_{rsf})\pi_{rsf} \geq 0 \quad \forall\, r \in R \tag{11a}$$

$$0 \leq u_{rsf} \perp \frac{1}{\Psi} P_{sf} - \theta_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{11b}$$

$$\zeta_r \in \mathbb{R}\ ;\ \sum_s \sum_f \theta_{rsf} = 1 \quad \forall\, r \in R \tag{11c}$$

$$0 \leq \theta_{rsf} \perp u_{rsf} - (\zeta_r - \pi_{rsf} x_r + C_r^{inv} x_r) \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{11d}$$

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

$$0 \leq g_{rtsf} \perp W_t C_r^{var} - \lambda_{tsf} + \mu_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{12a}$$

$$0 \leq y_{tsf} \perp W_t C^{cap} - \lambda_{tsf} \geq 0 \quad \forall\, t \in T, s \in S, f \in F \tag{12b}$$

$$0 \leq e_{rtsf} \perp \phi_{rtsf}^{soc} - \phi_{r,t+1,s,f}^{soc} + \phi_{rtsf}^{cap} - \xi_{r,t+1,s,f}^{d} \geq 0$$

$$\forall\, r \in O, t \in \{1, 2, ..., |T|-1\}, s \in S, f \in F \tag{12c}$$

$$0 \leq e_{r|T|sf} \perp \phi_{r|T|sf}^{soc} - \phi_{r1sf}^{soc} + \phi_{r|T|sf}^{cap} - \xi_{r1sf}^{d} \geq 0 \quad \forall\, r \in O, s \in S, f \in F \tag{12d}$$

$$0 \leq z_{rtsf}^{ch} \perp -F^{ch} \phi_{rtsf}^{soc} + \phi_{rtsf}^{c} + \phi_{rtsf}^{bal} + \lambda_{tsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{12e}$$

$$0 \leq z_{rtsf}^{dch} \perp \frac{1}{F^{dch}} \phi_{rtsf}^{soc} + \phi_{rtsf}^{d} + \xi_{rtsf}^{d} + \phi_{rtsf}^{bal} - \lambda_{tsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{12f}$$

$$\lambda_{tsf} \in \mathbb{R}\ ;\ D_{ts} - \big(\sum_r^{|G|} g_{rtsf} + \sum_r^{|O|} \left[z_{rtsf}^{dch} - z_{rtsf}^{ch}\right] + y_{tsf}\big) = 0 \quad \forall\, t \in T, s \in S, f \in F \tag{12g}$$

$$0 \leq \mu_{rtsf} \perp x_r A_{t,r} - g_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{12h}$$

$$\phi_{r1sf}^{soc} \in \mathbb{R}\ ;\ e_{r1sf} - (e_{r|T|sf} - \frac{1}{F^{dch}} z_{r1sf}^{dch} + F^{ch} z_{r1sf}^{ch}) = 0 \quad \forall\, r \in O, s \in S, f \in F \tag{12i}$$

$$\phi_{rtsf}^{soc} \in \mathbb{R}\ ;\ e_{rtsf} - (e_{r,t-1,s,f} - \frac{1}{F^{dch}} z_{rtsf}^{dch} + F^{ch} z_{rtsf}^{ch}) = 0$$

$$\forall\, r \in O, t \in \{2, 3, ...|T|\}, s \in S, f \in F \tag{12j}$$

$$0 \leq \phi_{rtsf}^{cap} \perp \frac{1}{N_r^s} x_r - e_{rtsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{12k}$$

$$0 \leq \phi_{rtsf}^{c} \perp x_r - z_{rtsf}^{ch} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{12l}$$

$$0 \leq \phi_{rtsf}^{d} \perp x_r - z_{rtsf}^{dch} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{12m}$$

$$0 \leq \xi_{r1sf}^{d} \perp e_{r|T|sf} - z_{r1sf}^{dch} \geq 0 \quad \forall\, r \in O, s \in S, f \in F \tag{12n}$$

$$0 \leq \xi_{rtsf}^{d} \perp e_{r,t-1,s,f} - z_{rtsf}^{dch} \geq 0 \quad \forall\, r \in O, t \in \{2, 3, ..., |T|\}, s \in S, f \in F \tag{12o}$$

$$0 \leq \phi_{rtsf}^{bal} \perp x_r - (z_{rtsf}^{dch} + z_{rtsf}^{ch}) \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{12p}$$

# D Numerical steps

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 instance of model (8) contains 49,032 continuous variables, 16 quadratic constraints, and 16 binary variables. All solutions were derived using the Gurobi solver run on cluster computing with 48-core Intel(R) Xeon(R) 2.10GHz CPUs and 180GB RAM. The main case featuring risk aversion, missing markets, and four scenarios solves in approximately 1,700 seconds. The same case solves in 100 seconds when using the "representative investor" formulation (resulting in the same solution), showcasing that this approach offers a computational advantage.

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## Author Contributions

Conceptualization, E.D.; Methodology, E.D. and S.A.G.; Investigation, E.D. and S.A.G.; Validation, E.D., S.A.G., L.R., M.K.; Writing – Original Draft, E.D.; Writing – Review & Editing, E.D., L.R., M.K., S.A.G.; Supervision, M.K.

## Declaration of Interests

None.

## 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. Economics of Energy & Environmental 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. Current Sustainable/Renewable Energy Reports URL: https://doi.org/10.1007/s40518-023-00223-4, doi:10.1007/s40518-023-00223-4.

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 Economics 120, 106567. doi: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. Applied Energy 321, 119356. doi:10.1016/j.apenergy.2022.119356.

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

DeCarolis, J.F., 2011. Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. Energy Economics 33, 145–152. doi: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. Renewable and Sustainable Energy Reviews 112, 797–812. doi: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. doi: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. doi:10.1016/j.enpol.2022.113395.

Ehrenmann, A., Smeers, Y., 2011. Generation Capacity Expansion in a Risky Environment: A Stochastic Equilibrium Analysis. Operations Research 59, 1332–1346. URL: http://pubsonline.informs.org/doi/abs/10.1287/opre.1110.0992, doi: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. US 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. The Journal of the Operational Research Society 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. volume 180 of *International Series in Operations Research & Management Science*. Springer, New York, NY. URL: https://link.springer.com/10.1007/978-1-4419-6123-5, doi: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. Journal of the Operational Research Society 57, 995–1004. doi:10.1057/palgrave.jors.2602052.

Grubb, M., Newbery, D., 2018. UK Electricity Market Reform and the Energy Transition: Emerging Lessons. The Energy Journal 39. URL: http://www.iaee.org/en/publications/ejarticle.aspx?id=3250, doi:10.5547/01956574.39.6.mgru.

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

Gérard, H., Leclère, V., Philpott, A., 2018. On risk averse competitive equilibrium. Operations Research Letters 46, 19–26. URL: https://www.sciencedirect.com/science/article/pii/S0167637717303383, doi:10.1016/j.orl.2017.10.011.

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 Transactions on Power Systems 33, 4819–4830. doi: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. doi: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. doi: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. Journal of Institutional Economics , 1–17URL: https://www.cambridge.org/core/product/identifier/S1744137421000400/type/journal_article, doi: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. doi: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. The Electricity Journal 31, 33–41. URL: https://www.sciencedirect.com/science/article/pii/S1040619017302816, doi:10.1016/j.tej.2017.12.001.

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. doi:10.1016/j.enpol.2017.01.029.

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. Applied Energy 275. doi:10.1016/j.apenergy.2020.115390. publisher: Elsevier Ltd.

Markowitz, H., 1952. Portfolio Selection. The Journal of Finance 7, 77–91. doi:10.1111/j.1540-6261.1952.tb01525.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/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. doi:10.1016/j.joule.2022.01.004.

Mays, J., Jenkins, J.D., 2023. Financial Risk and Resource Adequacy in Markets with High Renewable Penetration. Policy and Regulation IEEE Transactions on Energy Markets , 1–13URL: https://ieeexplore.ieee.org/abstract/document/10273857, doi:10.1109/TEMPR.2023.3322531. conference Name: Policy and Regulation IEEE Transactions on Energy Markets.

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

Meunier, G., 2013. Risk aversion and technology mix in an electricity market. Energy Economics 40, 866–874. doi: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.

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 Economics 64, 213–225. doi:10.1016/j.eneco.2017.03.025.

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

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

Neuhoff, K., May, N., Richstein, J.C., 2022. Financing renewables in the age of falling technology costs. Resource and Energy Economics 70, 101330. doi:10.1016/j.reseneeco.2022.101330.

Newbery, D., 2016. Missing money and missing markets: Reliability, capacity auctions and interconnectors. Energy Policy 94, 401–410. doi: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/.

Pineda, S., Boomsma, T.K., Wogrin, S., 2018. Renewable generation expansion under different support schemes: A stochastic equilibrium approach. European Journal of Operational Research 266, 1086–1099. doi:10.1016/j.ejor.2017.10.027. publisher: Elsevier B.V.

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. Applied Energy 236, 1249–1268. doi:10.1016/j.apenergy.2018.11.098.

Radner, R., 1970. Problems in the Theory of Markets under Uncertainty. The American Economic Review 60, 454–460. Publisher: American Economic Association.

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. doi: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. Electric Power Systems Research 214, 108725. doi:10.1016/j.epsr.2022.108725.

Rockafellar, R.T., Uryasev, S., 2002. Conditional value-at-risk for general loss distributions. Journal of Banking & Finance 26, 1443–1471. doi: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 Transactions on Power Systems 27, 752–761. doi: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. URL: https://www.sciencedirect.com/science/article/pii/S0360544221006204, doi: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 , 1–18URL: https://linkinghub.elsevier.com/retrieve/pii/S2542435118303866, doi:10.1016/j.joule.2018.08.006. publisher: Elsevier Inc.

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. Nature Energy 3, 341–346. URL: https://www.nature.com/articles/s41560-018-0121-4, doi:10.1038/s41560-018-0121-4. number: 4 Publisher: Nature Publishing Group.

Siddiqui, S., Gabriel, S.A., 2013. An SOS1-Based Approach for Solving MPECs with a Natural Gas Market Application. Networks and Spatial Economics 13, 205–227. doi: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. Elsevier. volume 15 of *Financial Engineering*, pp. 511–563. doi:10.1016/S0927-0507(07)15012-X.

Stiglitz, J.E., 1982. The Inefficiency of the Stock Market Equilibrium. The Review of Economic Studies 49, 241–261. URL: https://doi.org/10.2307/2297273, doi:10.2307/2297273.

Tanaka, M., Conejo, A.J., Siddiqui, A.S., 2022. Environmental Externalities, in: Tanaka, M., Conejo, A.J., Siddiqui, A.S. (Eds.), Economics of Power Systems. Springer International Publishing, Cham. International Series in Operations Research & Management Science, pp. 197–254. URL: https://doi.org/10.1007/978-3-030-92871-1_6, doi:10.1007/978-3-030-92871-1_6.

Tietjen, O., Pahle, M., Fuss, S., 2016. Investment risks in power generation: A comparison of fossil fuel and renewable energy dominated markets. Energy Economics 58, 174–185. doi: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 Transactions on Power Systems 28, 1531–1539. doi:10.1109/TPWRS.2012.2217510. conference Name: IEEE Transactions on Power Systems.

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 and Climate Change 4, 100110. doi:10.1016/j.egycc.2023.100110.

# Supplementary Information for "Consequences of the missing risk market problem for power system emissions"

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## 1 Implications of using representative time periods

The results reported in the main manuscript are derived from modeling the power system's operation over 30 representative days. Here, we test if our results change if we use an annual scope with 8,760 hourly time steps. We show results derived from full-year model runs in Table S1. The "Risk-neutral" and "Risk-averse & complete markets" cases are derived from running the optimization model (1) (see main manuscript). To generate results for the "Risk-averse & missing markets" case, we use the "representative investor" formulation (see main manuscript Section 2.3.2), because of its significant computational advantage. Recall that in this formulation, an investor can invest in all technologies. As discussed in the main manuscript, this formulation leads to the same result as our main formulation (one technology per investor) when using a 30-day temporal scope (see Section 3.6). For ease of comparison, we also include our results from the main manuscript below in Table S2.

We find that the directions in which technology capacities and emissions change between risk cases are the same across the two tables. A key difference concerns the impact of missing markets on gas capacity. In our main results (Table S2), gas capacity increases from 20.5 GW in the risk-neutral case (first row) to 22.5 GW in the missing markets case (second row). In contrast, this increase almost disappears in Table S1. Nevertheless, the percent share of gas capacity within the capacity mix increases non-negligibly in both tables. Thus in both tables, the investment mix shifts toward gas, and away from the clean energy technologies when markets for risk are missing.

| | Capacity mix Gas (GW) | Wind (GW) | Solar (GW) | Battery (GW) | Emissions ($MtCO_2$) |
|---|---|---|---|---|---|
| Risk-neutral | 20.9 | 26.8 | 10.1 | 1.2 | 13.0 |
| Risk-averse & missing markets* | 21.0 | 23.0 | 8.6 | 0.3 | 16.1 |
| Risk-averse & complete markets | 20.3 | 29.7 | 14.6 | 2.0 | 10.0 |

Table S1: Key results when using a full year
All models were run under both demand and gas price uncertainty.
*Results derived using the "representative investor" formulation (see main manuscript Section 2.3.2).

| | Capacity mix Gas (GW) | Wind (GW) | Solar (GW) | Battery (GW) | Emissions ($MtCO_2$) |
|---|---|---|---|---|---|
| Risk-neutral | 20.5 | 26.5 | 14.8 | 3.1 | 13.8 |
| Risk-averse & missing markets | 22.5 | 22.8 | 11.2 | 1.1 | 18.1 |
| Risk-averse & complete markets | 19.3 | 31.7 | 18.2 | 3.5 | 10.4 |

Table S2: Key results when using 30 representative days
All models were run under both demand and gas price uncertainty.

# 2 Additional sensitivity tests

Here, we test the sensitivity of the results to alternative price cap assumptions, which we report in Table S3. Tests with price caps of $100/MWh and $9,000/MWh did not alter the directions of our results with regard to emissions or the capacity mix, with the exception that, in the case of a $100/MWh price cap, gas capacity is lower in the missing markets case relative to the risk-neutral case, in contrast to our result above. This showcases that, as expected, gas investment is dependent on its ability to capture revenues from scarcity pricing events.

The next sensitivity test uses alternative assumptions for the degree of risk aversion, as represented by parameter $\Omega$. We test values of 0.25 and 0.75, which respectively represent higher and lower risk-aversion relative to our main results, which assume a value of 0.5. In all cases, we find the same directional impact of the missing markets case on all four technology capacities and emissions relative to risk neutrality. As expected, the magnitudes differ. The higher the degree of risk-aversion, the lower are the wind, solar, and battery capacities. The gas capacity equals 21.7, 22.5, and 21.5 GW for $\Omega$ of 0.25, 0.5, and 0.75 respectively. This pattern reflects the changing magnitudes of the already mentioned countervailing effects acting on gas capacity: on the one hand, risk exposure encourages less investment; and on the other hand, less competition from other technologies encourages more investment. Finally, we note that the alternative $\Omega$'s also do not alter the directionality of the effects of the complete market case, except that for $\Omega = 0.75$, solar capacity is less (though overall variable renewable capacity is still greater) than in the risk-neutral case.

| Resource | Risk case | Main results ($\Omega = 0.5$, price cap = \$2000/MWh) | Low risk aversion ($\Omega = 0.75$) | High risk aversion ($\Omega = 0.25$) | Price cap 100 (\$/MWh) | Price cap 9,000 (\$/MWh) |
|---|---|---|---|---|---|---|
| Gas | RN | 20.5 | 20.5 | 20.5 | 14.6 | 20.5 |
| | RA & MM | 22.5 | 21.5 | 21.7 | 12.5 | 21.7 |
| | RA & CM | 19.3 | 19.8 | 19.0 | 14.7 | 19.3 |
| Wind | RN | 26.5 | 26.5 | 26.5 | 28.3 | 26.5 |
| | RA & MM | 22.8 | 25.6 | 20.7 | 23.0 | 23.4 |
| | RA & CM | 31.7 | 30.6 | 32.0 | 32.8 | 31.7 |
| Solar | RN | 14.8 | 14.8 | 14.8 | 15.5 | 14.9 |
| | RA & MM | 11.2 | 13.3 | 10.1 | 14.8 | 10.8 |
| | RA & CM | 18.2 | 15.6 | 23.6 | 18.5 | 18.2 |
| Battery | RN | 3.1 | 3.1 | 3.1 | 0.0 | 3.1 |
| | RA & MM | 1.1 | 1.8 | 0.2 | 0.0 | 2.5 |
| | RA & CM | 3.5 | 3.2 | 3.6 | 0.1 | 3.5 |

Table S3: Technology capacity (GW) for alternative model parameters
RN: Risk-neutral; RA: Risk-averse; MM: Missing markets; CM: Complete markets

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