Financial Risk and Resource Adequacy in Markets With High Renewable Penetration

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***Abstract*—This article considers the evolution of electricity market design as systems shift toward carbon-free technologies. Growth in wind and solar generation is likely to lead to increased price volatility on diurnal and seasonal timescales. In the standard risk-neutral optimization framework, volatility does not pose any theoretical issues for market design. Because revenue volatility has the potential to lead to a higher cost of capital for investments in competitive markets, however, many observers have questioned the viability of competitive models for resource adequacy as wind and solar grow in importance. To assess the role of risk management in overall market performance, we construct a stochastic equilibrium model incorporating financial entities as hedge providers for investors in generation capacity. Unlike in the standard optimization framework, the cost of capital in the equilibrium framework is endogenously determined by interannual revenue volatility and the risk measures used by market participants. Surprisingly, exploratory numerical tests suggest that overall investment risk may be lower in systems dominated by variable renewables due to reduced exposure to fuel price uncertainty. However, changes in investment risk are not uniform across resource types, and increased risk for peaking and backup resources contributes to lower reliability in the modeled future systems.**

***Index Terms*—Equilibrium, market design, power systems, resource adequacy, risk trading.**

I. Introduction

MACRO-ENERGY systems models routinely reach the conclusion that the majority of electricity in deeply decarbonized systems will be supplied by weather-dependent and/or low or zero-marginal-cost resources like wind, solar, geothermal, and nuclear power [1]. Much higher levels of wind and solar may increase price and revenue volatility in future electricity systems and could pose a number of challenges for market design [2], [3], raising widespread concern that existing market structures will not support an efficient transition [4]. To a large degree, this skepticism represents a continuation of a longer-standing debate about the degree to which market operators can rely on decentralized investment decisions made by producers and consumers of electricity to lead to an efficient and reliable system. To date, very few systems have fully embraced the logic of competitive markets. Many areas remain vertically integrated, with generation capacity centrally planned and subject to rate regulation, while most nominally competitive systems place mandatory procurement requirements on retailers to ensure resource adequacy, e.g., through a centralized capacity market [5].

Growing discontent with the performance of these mandatory procurement requirements has prompted discussion of what might replace them. The underlying issue is that, due to flaws in short-term price formation, most energy markets fail to produce high enough prices to support investment over the long run. Without the threat of high prices, consumers of energy have insufficient incentive to enter forward contracts with generators, necessitating some form of mandatory purchase obligation. Accordingly, for advocates of a decentralized approach to resource adequacy, the first step is ensuring prices in the short-term markets that are strong enough to avoid the need for a separate resource adequacy construct [6]. The most forceful arguments for a centralized mechanism, meanwhile, also recognize that such prices are an important input to designing coherent long-term mechanisms [7], [8]. Others contend, however, that as a practical matter many jurisdictions will simply be unwilling to sustain the high scarcity prices necessary to make a decentralized model successful, necessitating a more direct approach to long-term procurement.

κάποιες δικαιοδοσίες μπορεί να μη θέλουν να έχουν ↑ prices για decentralized model to work.

This article proposes a model and conducts exploratory numerical tests to consider how the terms of this long-standing debate may change with a transition to carbon-free technologies. In the analytical framework descending from [9], the central logic of idealized competitive markets is invariant to technology [10]. However, embedded in that analytical framework is the assumption that the cost of capital for investors is invariant to revenue volatility. Given the effort expended on arranging contracts to ensure stable revenues for project finance, it would be surprising if this assumption held in practice. In this context, while restoring full-strength scarcity prices is necessary to the success of a decentralized framework, it is not sufficient. Success hinges on the presence of financial markets enabling risk trading over the long durations required for financing new assets. Since modeling of systems with high levels of variable renewables typically projects greater price volatility, it may be hypothesized that markets in risk will grow in importance as the technology mix changes. Correspondingly, the effect of incomplete markets in risk could be amplified in the future, motivating regulatory interventions to encourage or mandate risk sharing.

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Our approach is as follows. First, we construct an optimization model of an energy-only electricity market in the mold of [9], with the cost of capital exogenously specified. Next, building most directly from [11], we construct a stochastic equilibrium model describing a market with risk-averse investors and incomplete risk trading, in which the cost of capital is endogenously determined by the distribution of input random variables, the risk measures used by market participants, and the types and level of risk trading included. Using 18 years of data from the Electric Reliability Council of Texas (ERCOT), we then calibrate both stylized models so that they each result in a capacity mix resembling the more detailed optimization modeling of ERCOT given in [12]. Having tuned the equilibrium model in this way to identify plausible risk measures and trading volumes, we then modify the input costs of the resources available to the system to produce future scenarios with dominant shares of wind and solar power. The "constant cost of capital" optimization model is in effect guaranteed to succeed with these future technology costs. Our goal is to assess whether an increase in investment risk leads to degradation of consumer surplus in the "endogenous cost of capital" equilibrium framework.

As expected, thermal resources see a higher cost of capital in the future cases due to greater concentration of inframarginal rents in fewer of the modeled weather years. This concentration of net revenues leads to greater investment risk for these resources, less installed capacity, and lower reliability in the future cases. Surprisingly, however, fleet-wide investment risk actually decreases with the future technology costs under the calibrated parameters. Wind and solar see a lower cost of capital, as their exposure to fuel price risk diminishes with thermal resources setting prices less often. Since the clean technologies receive the majority of capital investment in the future cases, the net effect is a reduction in the total risk premium paid by consumers. Caution is warranted in interpreting these modeling results, which we do not expect to be fully general. More important than the results themselves is our effort to be precise about the assumptions required to achieve them. With this precision, we hope to add nuance to debates about whether markets will "break and thus require a fundamental rethink" [10] in the transition to carbon-free resources. In our results, the market can hardly be described as broken: consumer surplus in the equilibrium, incomplete markets framework increases relative to what we would expect in the optimization framework. At the same time, the results indicate growing challenges to ensuring resource adequacy in a market context and invite further analysis on different test systems or using different assumptions.

Perhaps the most important caveat for interpreting the results is that, in calibrating to the optimization results of [12], our study assumes by design that risk is manageable in current energy-only markets. The belief that current decentralized markets achieve efficient levels of reliability is by no means universally shared, and has received even more scrutiny in the wake of the shortages experienced in ERCOT during severe weather in February 2021. With a similar modeling approach to this article's, [13] argues that the implied cost of capital for incremental investments protecting against rare "tail events" may be substantially greater than that assumed for typical investments in generation capacity.

At least four areas for further inquiry emerge from the study. First, in both the present and future mixes, annual revenues for peaking generators in energy-only markets exhibit substantial positive skewness. It is thus important to refine estimates of how the distribution of revenues may evolve over time, as well as how investors may respond. Second, if estimates of the value of lost load (VOLL) are held constant, a shift to variable technologies implies that it is efficient to shed firm load more often than in present systems despite significant growth in responsive demand. An increase in the VOLL to compensate would lead to an increase in skewness of annual generator revenues. Third, most modeling indicates that managing risks in systems reliant on variable technologies depends on aggregating a large portfolio of assets with diverse performance characteristics. A financial consequence is that there may be greater benefit to multilateral risk sharing mechanisms in future energy markets, as opposed to the bilateral hedging mechanisms which are dominant today. Fourth, while the discussion focuses on the viability of decentralized approaches, it is likely that many systems will continue to use some form of centralized mechanism for resource adequacy. Since the success of any centralized approach will rely in part on its ability to efficiently allocate risk across market participants, the modeling approach could be useful in the context of designing such a mechanism. Since current centralized capacity mechanisms offer an incomplete set of risk hedging products [11], they may not adequately support systems dominated by low-carbon resources.

Section II describes the strongest arguments for why some form of central planning may be required for resource adequacy in electricity markets. The "constant cost of capital" optimization model is developed in Section III, followed by the "endogenous cost of capital" equilibrium model in Section IV. Results of the numerical study are discussed in Section V, and Section VI concludes.

(why some form of central planning may be required)

II. Risks to the Decentralized Framework

A common but imprecise statement of the primary concern about the future viability of competitive electricity markets is that, since the clearing price of electricity is determined by marginal cost and the marginal cost of wind and solar is zero, the growth of these resources (along with other zero- or low-marginal-cost resources such as geothermal and nuclear power) will cause electricity prices to collapse and lead to insufficient incentives for future deployment of needed resources. This line of reasoning is incomplete for two reasons. First, while it is clear that wind and solar lead to lower prices when their output is high, both theoretical and empirical evidence suggests that their effect on average prices is muted [14]. Second, in the basic model of theoretically ideal markets [9], if prices fall below the level required to support deployment of a resource, it simply indicates that the resource in question is not needed by the system. In this context, several authors have made the observation that variability and zero (or even negative) marginal costs do not change the logic of idealized competitive markets [6], [10], [15].

More precise versions of the concern therefore focus on ways in which the expansion of wind and solar could exacerbate imperfections already present in real-world implementations of the theoretical ideal. Three possible lines of argument are as follows:

1) Due to price and offer caps used to mitigate market power, as well as the difficulty of pricing intertemporal constraints and certain actions taken by system operators to guarantee reliability, prices in energy markets are suppressed below the level needed to support an efficient capacity mix [16]. Growth of variable renewables could exacerbate this suppression, leading to greater reliance on supplementary revenue streams to ensure resource adequacy [14]. Existing resource adequacy constructs may not be equipped to the task of supporting a transition because they preferentially support financing of technologies with higher marginal costs [11], do not adequately address the need for flexibility [17], and may be more subject than short-term markets to pressures of deregulatory capture [18], through which incumbents can steer market rules to their own advantage [19]. Designing resource adequacy mechanisms that resolve these issues without fixing the underlying flaws in short-term price formation amounts to a new form of centrally-organized integrated resource planning. In this context, skepticism about the future viability of markets equates to a belief that systems will fail to address underlying flaws in short-term price formation.
2) If markets do manage to address flaws in short-term energy market prices, it could imply a substantial increase in investment risk. Modeling of energy-only markets regularly shows that annual revenues exhibit extreme positive skewness, with investors recovering fixed costs in a relatively small number of hours of supply scarcity [12]. Projections of systems with high levels of renewables predict an increased frequency of these scarcity events [20]. Given the risk associated with such positive skewness, restoring price volatility without ensuring conditions for long-term risk sharing could lead to a higher cost of capital for investors and poor market outcomes overall [21], [22]. Given that regulators may hesitate to rely on what some might consider irrational exuberance to guarantee resource adequacy, it is important to understand attitudes toward risk and the health of markets for risk trading.
3) Even if an optimal long-run capacity mix would heavily feature variable renewables, decarbonization ambitions may dictate a pace of transition that is faster than would occur on normal investment timescales. This mismatch could imply persistent out-of-market policy support for multiple technologies, leading to a question of whether markets as currently designed will be the most efficient way to attract investment in resources that do not enjoy current policy support [4]. While we do not directly address this question in the present article, it bears mentioning that out-of-market subsidies do not pose any issues in partial equilibrium models incorporating a constant cost of capital: when a new subsidy regime is incorporated, the market simply shifts to a new equilibrium incorporating the lower prices implied by the subsidies, similarly to how equilibrium adjusts to changes in fuel or technology costs. While this shift may entail distributional consequences, reduced input costs cannot degrade total surplus within the market. Accordingly, skepticism about the viability of a residual market for unsubsidized resources instead rests on the possibility that the threat of future subsidies to competitors will exacerbate the uncertainty in future revenues for unsubsidized resources, leading to an increase in the hurdle rate for investors.

Our focus is on the second of these arguments. Since the introduction of competitive markets, substantial effort has gone into understanding the impact of long-term contracts for risk sharing on market outcomes, leading to a rich literature on stochastic equilibrium models with incomplete financial markets [11], [23], [24], [25], [26], [27]. Consumers of electricity, and the retailers that serve them, are exposed to price risk in the opposite direction from generators and would in principle be natural counterparties for long-term contracts. However, asymmetric information, transaction costs, and other frictions can prevent an ideal risk allocation between buyers and sellers [28]. While the phenomenon of insufficient demand-side interest in hedging is common to all commodity markets [29], it may be particularly acute in electricity because retailers have downside protection in the form of rolling blackouts, which reduce their obligations in scarcity events [30]. In energy-only markets like the Electric Reliability Council of Texas (ERCOT) and the Australian National Electricity Market, one solution to insufficient hedging has been a shift toward vertical integration, with companies operating both generation assets and a competitive retail entity [31]. Instead of contracts with loads or retailers, marginal entrants into the capacity mix in US markets are typically supported by hedging arrangements with banks [32], [33].

τι εννοεί με το downside protection;

The key differences between our model and those in the prior literature on stochastic equilibrium stem from these observations. The first difference is that financial institutions, rather than loads or retailers, act as hedge providers for marginal investors in generation. The main consequence of this modeling choice is to ensure that generators and storage sacrifice some expected return when they enter into contracts. A second difference is our effort to include a broader variety of contract forms tailored to the resources in the market, as observed in real-world markets. A third difference is the inclusion of electricity storage (e.g., batteries), which introduces intertemporal constraints that complicate the identification of an equilibrium. The fourth difference between our model and prior stochastic equilibrium models is scale: we include 18 years of hourly data on demand, wind, and solar availability in our numerical examples (for $18 \cdot 8760 = 157,680$ hours), relative to the 89 representative time periods used in [11].

πως τα financial institutions προσφέρουν hedge?

Two separate lines of argument for mandatory long-term contracts beyond that pursued in this article warrant mention. The first emphasizes their potential to reduce incentives to exercise market power in the short term [34]. While we assume perfect competition through this article, a transition to variable and opportunity-cost based resources is likely to also have implications for the future evolution of strategies for market power mitigation. The second, motivated by the electricity crisis in ERCOT in February 2021, is that such contracting may improve resilience to extreme events. For an uncontracted generator, a failure to produce during scarcity events leads to large lost opportunity costs but zero cash flow; for a contracted generator, a failure to deliver on obligations leads to concrete penalty payments. Assuming risk aversion, a contracted generator may therefore be more likely to take steps to guarantee availability during scarcity [13].

III. Constant Cost of Capital Model

Here we formulate a two-stage stochastic program describing a capacity expansion problem in which investment decisions are made in the first stage and operational decisions for one year in the second. Uncertainty comes from two elements. The random vector C^{EN}, with scenarios indexed by $f \in \mathcal{F}$, incorporates the fuel cost of each technology, while the random vector (A, D^{fix}), with scenarios indexed by $s \in \mathcal{S}$, indicates the availability of each generator as well as the non-price-responsive load in each hour of the year. These sources of randomness are assumed to have finite support, and we indicate the probability of scenario (f, s) with p_{fs}.

A. Dispatch

We begin by defining a perfectly competitive economic dispatch problem covering one year of operations with the outcomes of all random variables known, i.e., the second stage of the problem. Several simplifications to the true operational problem are made for the sake of computational convenience in the equilibrium model developed in Section IV. To avoid defining extra notation for features that could be more readily added in the optimization setting, we mention these simplifications here. First, a single agent will be responsible for investment and financial trading decisions for each technology. Second, the model represents load as a single entity and παραλειπει omits unit commitment constraints and ramping constraints for generators, as well as conversion losses for storage. Third, decisions within the operational stage are made with perfect foresight. Given these simplifications, we do not provide a detailed description of the hourly prices arising in the modeled systems; price duration curves in future systems are investigated in more detail in [35] and [36]. Instead, given our interest in long-term investment decisions, the primary intent of the model is to capture the distribution of annual revenues. While we assume these simplifications have limited impact on the timescale of interest, understanding the importance of each of these for price formation and price volatility is an important area for further work. Alternative approaches to modeling investment equilibria, such as the agent-based simulation proposed in [37], may offer a more promising route to including more detailed operational constraints in the analysis.

1) Notation:

Set:

$f \in \mathcal{F}$:	set of scenarios for fuel prices.
$g \in \mathcal{G}$:	set of all generation technologies.
$j \in \mathcal{J}$:	set of all storage technologies.
$i \in \mathcal{I} = \mathcal{G} \cup \mathcal{J}$:	set of all technologies.
$s \in \mathcal{S}$:	set of scenarios for generator availability and demand profiles.
$t \in \mathcal{T}$:	set of time periods.

Parameters:

B:	value of non-price-responsive load (\$/MWh)
$\hat{C}_i^{INV}$:	investment cost for technology i, annualized at exogenous cost of capital (\$/MW)
D_t^{res}:	amount of price-responsive demand, which bids at a value declining linearly from B to 0 (MW)
L_t:	length of time period t, assumed to be one hour (hr)
Q_j:	conversion factor for duration of storage j (MW/MWh)

Scenario-specific parameters (i.e., realizations of random variables):

A_{gst}:	availability of generator g in time period t under profile scenario s ($\%$)
C_{fg}^{EN}:	marginal cost for generator g under fuel price scenario f (\$/MWh)
D_{st}^{fix}:	baseline level of non-price-responsive load in time period t in profile scenario s (MW)

First-stage decision variables:

x_i:	quantity installed of technology i (MW)

Second-stage decision variables:

y_{gt}:	production by generator g in time period t (MW)
z_{jt}:	net injection from storage j in time period t (MW)
w_{jt}:	state of charge for storage j at end of time period t (MWh)
d_t^{fix}:	non-price-responsive demand cleared in time period t (MW)
d_t^{res}:	responsive demand cleared in time period t (MW)

2) Formulation: The second-stage problem is a year-long economic dispatch given first-stage investment decisions x, with H_{fs} denoting the total surplus given scenarios f for fuel price and s for generator availability and demand. The model is stated as follows:

$$(ED)_{fs}$$

$$\max_{d,w,y,z} H_{fs} = \sum_{t \in \mathcal{T}} L_t B \left(d_t^{fix} + d_t^{res} - (d_t^{res})^2 / (2 D_t^{res}) \right) - \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} L_t C_{fg}^{EN} y_{gt} \tag{1a}$$

s.t.

$$d_t^{fix} + d_t^{res} = \sum_{g \in \mathcal{G}} y_{gt} + \sum_{j \in \mathcal{J}} z_{jt} \qquad \forall t \in \mathcal{T} \tag{1b}$$

$$0 \leq y_{gt} \leq A_{gst} x_g \qquad \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{1c}$$

$$w_{j,t-1} - L_t z_{jt} = w_{jt} \qquad \forall j \in \mathcal{J}, t \in \mathcal{T} \tag{1d}$$

$$0 \leq Q_j w_{jt} \leq x_j \qquad \forall j \in \mathcal{J}, t \in \mathcal{T} \tag{1e}$$

$$-x_j \leq z_{jt} \leq x_j \qquad \forall j \in \mathcal{J}, t \in \mathcal{T} \tag{1f}$$

$$0 \leq d_t^{fix} \leq D_t^{fix} \qquad \forall t \in \mathcal{T} \quad (1g)$$

$$0 \leq d_t^{res} \leq D_t^{res} \qquad \forall t \in \mathcal{T}. \quad (1h)$$

The objective in (1a) includes a quadratic term describing the value of price-responsive load (elastic demand) and linear terms for the value of non-price-responsive load (emergency involuntary demand curtailment or rolling blackouts) and the cost of producing power. Equation (1b) enforces power balance, while (1c) limits generators to produce no more than the amount available given the installed capacity and the realization of the random variable A_{gst}. With an appropriate adjustment for the state of charge at the beginning of the year, (1d) and (1e) ensure consistency for the state of charge of storage. To limit end-of-horizon effects, (1d) is defined to be circular in numerical tests. The lone storage technology included in the numerical tests is a 1-hour battery, such that the net injection from storage in any hour is limited by its state of charge. Accordingly, the redundant constraint in (1f) can be dropped in our numerical tests. While this choice was made primarily for computational convenience, initial tests suggested that the energy rating of the storage resource dominated its total value in future systems; accordingly, with appropriate unit conversions, the modeled resource could be interpreted in terms of its cost per MWh.

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circular είναι [illegible] των simulations

energy rating of battery was the most critical factor in determining its economic value. $/MWh → straightforward economic evaluation of storage } από εκεί?

B. Capacity Expansion

Employing the variable H_{fs} defined in (1) as the surplus arising in the second stage of the problem, the full capacity expansion problem can be written as follows:

$$(OP) \qquad \max_{x \geq 0} \quad -\sum_{i \in \mathcal{I}} \hat{C}_i^{INV} x_i + \sum_{f \in \mathcal{F}} \sum_{s \in \mathcal{S}} p_{fs} H_{fs}. \tag{2}$$

Here the parameter $\hat{C}_i^{INV}$ indicates an annualized investment cost using an estimated weighted average cost of capital. Replacing H_{fs} with the objective function from $(ED)_{fs}$ and adding constraints for each scenario (f, s) gives a convex quadratic extensive form stochastic program. While we omit network constraints, the linear approximations of network flows typically used for electricity market clearing and analysis preserve convexity. Due to the assumed convexity, it can readily be shown that prices λ_{fst}, calculated as the dual variables associated with the power balance constraints in (b), provide the correct amount of revenue to support an optimal solution to model (2). Since the marginal cost C_{fg}^{EN} and generator availability A_{gst} are simply parameters in this model, this result does not change with the introduction of zero-marginal-cost or variable generators.

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why?

IV. Endogenous Cost of Capital Model

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In this section we modify the model in [11] to construct a two-stage stochastic equilibrium model that offers a different interpretation of the cost of capital. Instead of using an exogenous estimate, the model computes an endogenous cost of capital that results from the risk-free rate, underlying volatility in net revenue (i.e., revenue minus operating cost), the risk preferences of investors and financial traders, and the results of any financial trades. If we were willing to assume that markets

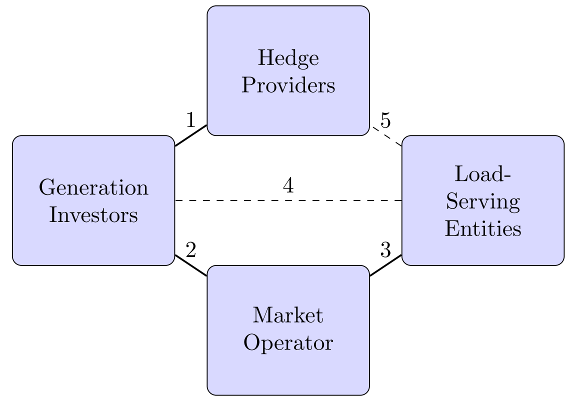

Fig. 1. Relationship of agents in the equilibrium model. Solid lines (1), (2), and (3) represent explicit financial transactions, whereas dashed lines (4) and (5) represent implicit trades that may affect the risk parameters calibrated in our numerical study but are not directly modeled. A consequence of the chosen structure is that the decisions of marginal entrants into the capacity mix are driven by the risk preferences of the hedge providers.

include a complete set of instruments for long-term risk trading with no transaction costs, this equilibrium problem could be reformulated as a risk-averse optimization problem [24], [25]. Instead, we specify a small set of instruments with constrained transaction volumes. While real-world projects encounter a much broader set of risks, the model includes only risk arising due to the volatility of prices in the spot market.

Fig. 1 depicts the overall structure of the equilibrium model described in this section. We highlight a key structural difference from the prior literature in that the risk preferences of end consumers are not explicitly modeled. Instead, the risk attitudes of hedge providers (e.g., banks) with no other modeled exposure to electricity prices heavily influence contract prices and therefore investment decisions.

A. Contracts

In order to reduce the risk of investments made in the first stage, investors in generation and storage can trade a variety of instruments that settle against the spot prices that arise in the second stage. Here we define a set of contracts $\mathcal{K}$. Let λ_{fst} be the price of energy in hour t given fuel price f and profile s, calculated as the dual variable corresponding to the power balance constraint in (1b), and let η_{fs}^k represent the payout of contract $k \in \mathcal{K}$ given this scenario.

The numerical studies use three classes of contracts. While real-world investors can combine different instruments, to simplify interpretation we specify one contract tailored to the risk profile of each technology. A heat rate call option [32], also called a spark spread option, is employed for the thermal technologies and gives the purchaser the right to buy power from a generator at a price that tracks its underlying fuel cost. When k indexes a heat rate call option covering all hours for generator g, the payout is calculated

$$\eta_{fs}^k = \sum_{t \in \mathcal{T}} L_t \max\{0, \lambda_{fst} - C_{fg}^{EN}\}. \tag{3}$$

* ποιανού payouts οι gen → τι αγοράζουν οι [illegible]?

A unit contingent contract, used for the variable technologies, is a futures contract in which the volume of the trade tracks the availability of sun or wind at the given location. When k indexes a unit contingent contract for generator g that pays price λ^k, the payout is calculated

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$$\eta_{fs}^k = \sum_{t \in \mathcal{T}} A_{gst} L_t \left(\lambda_{fst} - \lambda^k \right). \tag{4}$$

A revenue put, defined for storage resources, guarantees a minimum net revenue from energy sales over the course of a year. With μ_{fjst} as the dual variable corresponding to the state of charge constraint in (1e), annual net revenue per unit of storage j under scenario (f,s) can be calculated as $\pi_{fjs} = \sum_{t \in \mathcal{T}} \mu_{fjst}$. Then, when k indexes a revenue put for storage technology j guaranteeing net revenue at the level $\underline{C}_j^{INV}$, the payout is calculated

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payout covers the difference. It is design to protect against the risk of lower than expected revenue

$$\eta_{fs}^k = \max \left\{ 0, \underline{C}_j^{INV} - \pi_{fjs} \right\}. \tag{5}$$

↳ investment cost?

B. Market Participants

We construct models for two classes of market participants: investors in generation and storage and providers of hedge contracts. The risk attitude of market participants is characterized by a weighted sum of the expected value of profit, with weight β, and conditional value at risk (CVaR) of the α-level tail of profit, with weight $1-\beta$. This convex combination is a coherent risk measure, facilitating its inclusion in a mathematical optimization model [38], [39]. Investors in generation and storage resources solve a linear program to determine a quantity of financial contracts that maximizes risk-adjusted profit, while hedge providers solve a linear program that prices these contracts. The models incorporate generator and storage capacities, dispatch outcomes for each scenario, and contract prices and payouts as fixed parameters in these models. We define notation here that will be used by both classes.

1) Notation:

Set:

$a \in \mathcal{A}$	set of market participants.
$h \in \mathcal{H} \subset \mathcal{A}$	set of hedge providers.
$k \in \mathcal{K}$	set of contracts.

Parameters

α_a	tail probability at which CVaR is evaluated by market participant a, $0 < \alpha_a \leq 1$
β_a	weight given to expected value in risk measure for market participant a, $0 \leq \beta_a \leq 1$
ρ_a	risk measure for market participant a
$\underline{v}_a^k, \bar{v}_a^k$	minimum and maximum volume of contract k to be purchased or sold by market participant a (MW)
p_{fs}	nominal probability of scenario (f,s)
$\underline{C}_i^{INV}$	investment cost for technology i, annualized at risk-free rate (\$/MW)

Provisional parameters (i.e., values calculated by other agents):

λ_{fst}	price of energy in hour t under scenario (f,s) (\$/MWh)
π_{fis}	operating profit for generation or storage resource i under scenario (f,s) (\$/MW)
η_{fs}^k	payout of contract k under scenario (f,s) (\$/MW)
ϕ^k	price of contract k incurred in the first stage (\$/MW)

Variables

v_a^k	volume of contract k purchased or sold by market participant a (MW)
r_a	auxiliary variable equal to VaR for market participant a at the optimal solution (\$)
u_{fs}^a	surplus for market participant a under scenario (f,s) (\$)
u_{fs}^{a+}	auxiliary variable used in calculation of VaR (\$)

2) Investor Model: We distinguish between different agents by using $i \in \mathcal{A}$ for investors in generators and storage and $h \in \mathcal{A}$ for hedge providers. In the case of generation and storage, a single agent will be responsible for each technology. Given the assumption of perfect competition, the resulting decisions are equivalent to those that would arise from a large number of identical firms. The problem faced by project investors is stated as follows:

$(INV)_i$

$$\max_{v_i, u^i, u^{i+}, r_i} \rho_i = (1-\beta_i) \left[r_i - 1/\alpha_i \sum_{f \in \mathcal{F}} \sum_{s \in \mathcal{S}} p_{fs} u_{fs}^{i+} \right] + \beta_i \left[\sum_{f \in \mathcal{F}} \sum_{s \in \mathcal{S}} p_{fs} u_{fs}^i \right] \tag{6a}$$

s.t.

$$u_{fs}^i = -\underline{C}_i^{INV} x_i - \sum_{k \in \mathcal{K}} v_i^k \left(\phi^k - \eta_{fs}^k \right) + \pi_{fis} x_i \quad \forall f \in \mathcal{F}, s \in \mathcal{S} \tag{6b}$$

$$r_i - u_{fs}^i \leq u_{fs}^{i+} \quad \forall f \in \mathcal{F}, s \in \mathcal{S} \tag{6c}$$

$$0 \leq u_{fs}^{i+} \quad \forall f \in \mathcal{F}, s \in \mathcal{S} \tag{6d}$$

$$\underline{v}_i^k \leq v_i^k \leq \bar{v}_i^k \quad \forall k \in \mathcal{K}. \tag{6e}$$

Investors maximize a convex combination of CVaR and expected value of profit. Constraint (6b) calculates profit in every scenario resulting from the sale of contracts in the first stage and energy in the second. Net revenue from operations π_{fjs} was previously defined for storage for use in (5). For generator g, with ν_{fgst} as the dual variable to the maximum generation constraint in (1c), operating profit under scenario (f,s) can be calculated as $\pi_{fgs} = \sum_{t \in \mathcal{T}} A_{gst} \nu_{fgst}$. Constraints (6c) and (6d) determine the value of auxiliary variables used in the CVaR calculation. Constraint (6e) sets a maximum volume that can be bought or sold for each contract and guarantees that the investor problems are bounded.

3) Hedge Provider Model: Characterizing the supply of hedge contracts is a complicated problem. Whereas the "complete trading" benchmark assumes Arrow–Debreu securities

↳ complete trading

τι εννοεί;

corresponding to each possible state of the world, we instead limit the set of contracts to a smaller set drawn from the classes defined in Section IV-A. Our approach is to assume we can identify the marginal hedge provider for each contract and set contract prices equal to the marginal risk-adjusted value of the contract to that hedge provider's portfolio, as measured by a coherent risk measure ρ_h. The hedge provider's problem is stated as follows:

$$(HED)_h$$

$$\max_{u^h, u^{h+}, r_h} \rho_h = (1 - \beta_h) \left[r_h - 1/\alpha_h \sum_{f \in \mathcal{F}} \sum_{s \in \mathcal{S}} p_{fs} u_{fs}^{h+} \right] + \beta_h \left[\sum_{f \in \mathcal{F}} \sum_{s \in \mathcal{S}} p_{fs} u_{fs}^{h} \right] \tag{7a}$$

$$\text{s.t.} \quad u_{fs}^h = - \sum_{k \in \mathcal{K}} v_h^k \left(\phi^k - \eta_{fs}^k \right) \qquad \forall f \in \mathcal{F}, s \in \mathcal{S} \tag{7b}$$

$$r_h - u_{fs}^h \leq u_{fs}^{h+} \qquad \forall f \in \mathcal{F}, s \in \mathcal{S} \tag{7c}$$

$$0 \leq u_{fs}^{h+} \qquad \forall f \in \mathcal{F}, s \in \mathcal{S} \tag{7d}$$

$$\underline{v}_h^k \leq v_h^k \leq \bar{v}_h^k \qquad \forall k \in \mathcal{K}. \tag{7e}$$

Models for the investors and hedge providers differ in that the investment cost and operating profit in (6b) do not appear in (7b). Inclusion of risk-averse consumers creates an interpretation challenge in previous stochastic equilibrium models of capacity expansion, since it is not clear in advance which agent's risk attitude will drive the results. Our model makes the simplifying assumption that the marginal hedge provider has no other exposure to electricity prices. In principle, a more detailed model could be constructed with hedge providers acting as an intermediary between generators and retailers and loads. For our purposes, the important outcome is that the net position of hedge providers is such that generators will pay a risk premium in order to enter into contracts, and that the size of this premium will grow with the volatility of the underlying revenue stream.

A second difference is that contract volumes enter the hedge provider model as exogenous parameters determined by the solutions to the investor models, rather than decision variables. Instead of seeking a set of prices that clears the financial markets, the algorithm enforces consistency in volumes and then finds an implied price. Solving a risk-averse problem with a coherent risk measure is equivalent to solving a risk-neutral problem in which nominal scenario probabilities have been adjusted to place more weight on scenarios with negative outcomes [38]. In the hedge provider model, the CVaR calculation identifies the worst $(100 \cdot \alpha)$ percent of second-stage outcomes and gives higher weight to those scenarios. When scenario utility u_{fs}^h is within the α-level tail of profit, (7c) is binding and the dual variables τ_{fs} can be used to calculate this adjusted weighting. The marginal risk-adjusted value θ^k of contract k to hedge provider h can then be calculated as

dual variables ποιού constraint;

$$\theta^k = \sum_{f \in \mathcal{F}} \sum_{s \in \mathcal{S}} (\tau_{fs} + \beta_h p_{fs}) \eta_{fs}^k. \tag{8}$$

Algorithm 1: Solution Approach

Input: An instance of (EQ) defined by models (ED), (INV), and (HED).
Output: near-equilibrium solution to (EQ)
  define $\gamma, \delta, \varepsilon > 0$; let $\rho_a = 0 \; \forall a \in \mathcal{A}$; initialize x, ϕ
  loop outer
    $x_i \leftarrow \max\{0, x_i + \gamma \rho_i / \underline{C}_i^{INV}\} \quad \forall i \in \mathcal{I}$
    solve $(ED)_{fs}$; update
    $\lambda_{fst}, \pi_{fis}, \eta_{fs}^k \; \forall (f,s) \in \mathcal{F} \times \mathcal{S}, k \in \mathcal{K}$
    loop inner
      solve $(INV)_i \quad \forall i \in \mathcal{I}$
      $v_h^k \leftarrow -\sum_{i \in \mathcal{I}} v_i^k \quad \forall h \in \mathcal{H}, k \in \mathcal{K}_h$
      solve $(HED)_h$; update $\theta^k \quad \forall h \in \mathcal{H}, k \in \mathcal{K}_h$
      if $\max_{k \in \mathcal{K}} |\phi^k - \theta^k| < \varepsilon$ **then**
        break
      else
        $\phi^k \leftarrow \theta^k \quad \forall k \in \mathcal{K}$
      end if
    end loop
    if $\max_{i \in \mathcal{I}} |\rho_i| < \delta$ **then**
      return x and ϕ
    end if
  end loop

C. Solution Approach

Given perfect competition, equilibrium requires that the spot market clears in every hour of every year-long scenario, financial trades are balanced, and the risk-adjusted profit $\rho_i = 0$ for every technology. Algorithm 1 describes the decomposition approach used to identify capacity quantities x and contract prices ϕ that solve the equilibrium problem, which we label (EQ). Tolerance δ is used as a stopping criterion for capacity quantities, while ε is used for contract prices. As in [11], the outer loop updates capacity quantities using the step size parameter γ, while the inner loop sets contract prices. Relative to [11], however, identification of contract prices is simplified. By constructing the system such that each specific contract is only offered by one hedge provider and defining the sets $\mathcal{K}_h \subseteq \mathcal{K}$ to contain the contracts offered by hedge provider h, contract prices ϕ^k can be set equal to the marginal risk-adjusted value θ^k for the relevant hedge provider.

γιατί $\rho_i = 0$ κάθε tech. (τι σημαίνει το κέρδος;)

Εννοεί ότι ένας hedge μπορεί να έχει πολλά contracts αλλά του ίδιου είδους;

Although convergence cannot be guaranteed, we were able to obtain solutions with near-zero risk-adjusted profit by experimenting with the step size γ. While the models are a heavily stylized representation of reality, they are nevertheless far more complicated than the narrow cases on which uniqueness of equilibria can be shown [27]. While we performed limited tests from different starting points in an attempt to identify alternate equilibria, the potential for multiple equilibria remains an important topic for further inquiry [40].

V. Numerical Study

To assess the importance of risk trading to investment outcomes, we construct a test system using 18 years of wind, solar, and load data for ERCOT with hourly resolution. Historical demand is for years 2002–2019 is from ERCOT, while wind and solar time series are simulated output from Renewables.ninja derived from reanalysis models and satellite observations [41], [42]. Solar irradiance data is converted into power output using the Global Solar Energy Estimator model [43] and wind speeds are converted into power output using the Virtual Wind Farm model [44]. We produce two wind time series to capture differences in prevailing wind patterns across the state: one representing the average of capacity factors at three locations across the interior portions of Texas and one representing the average of three sites along Texas's Gulf Coast. One solar series consists of the average of capacity factors at three sites across the state. These 18 years constitute the scenarios indexed by $s \in \mathcal{S}$. We use two scenarios for fuel prices, giving a total of 36 a-long second-stage scenarios.

The coastal wind, interior wind, and solar resources are supplemented by three dispatchable or "firm" resources: a baseload technology (e.g., combined cycle gas turbine), peaking technology (e.g., open cycle gas turbine), and a high-marginal-cost backup technology (e.g., demand response), each of which are assumed to have availability $A_{gst} = 0.95$. Given this simplification, the model underestimates the potential for scarcity prices arising from correlated thermal outages or contingencies. The system also includes a 1-hr storage technology; since results are driven by the energy capacity needs, rather than the charge/discharge power rating, the choice of duration is less important than the assumed capital cost.

By changing the investment and fuel costs of the input technologies, we create three cases: the first a base case aimed at approximating the current mix observed in the system, the second with a high variable renewable energy (VRE) share of total energy, and a third removing the baseload and peaking technologies entirely, leading to an extreme VRE contribution. Given the stylized nature of the model, it should be understood that neither the high-VRE nor the extreme-VRE case is intended to be a projection of future outcomes. Moreover, since the base case is trying to approximate the current mix, which is rapidly changing and cannot be said to be in a long-run equilibrium, costs in the base case do not reflect the actual cost of recent projects. Given these caveats (Επιφυλάξεις), our discussion emphasizes the directional impacts that high levels of VRE could have on financial and reliability outcomes rather than assessing the magnitude of those impacts.

Seven financial contracts are defined corresponding to the seven technologies: unit contingent contracts for each of the variable resources, heat-rate call options for each of the three firm generators, and a revenue put for the storage technology. To allow greater control in the model, technologies are limited to only trading the contract specifically designed for them; i.e., $\underline{v}_i^k = \overline{v}_i^k = 0$ for all other contracts. The value of lost load $B =$ \$9,000/MWh, and the quantity of responsive demand $D_t^{res} =$ 500 MW. In general, higher levels of responsive demand can reduce price volatility [35]. Given that one interpretation of our modeled backup resource is as demand response, we limit the assumed price-responsive demand to this relatively low level (500 MW) and then allow the model to determine how much additional backup resource capacity is installed endogenously.

The models are implemented in AMPL and solved using Gurobi.

A. Two Representations of the Current Mix

To construct a base case, our goal was to identify plausible values for risk parameters α and β, trade limits $\underline{v}_i^k$ and $\overline{v}_i^k$, investment costs $\underline{C}_i^{INV}$, and energy costs C_{fg}^{EN} to lead to outcomes similar to those resulting from the detailed modeling of ERCOT performed in [12]. Three outcomes are particularly important for our purposes: the distribution of annual net revenues, expected unserved energy, and the total share of energy provided by VRE. We choose $\alpha_i = 0.1$ and $\beta_i = 0.4$; in project finance terms, this risk measure can be interpreted as arising from risk-averse debt investors supplying 60% of capital and risk-neutral equity investors providing the remaining 40%. A single hedge provider uses $\alpha_h = 0.9$ and $\beta_h = 0.2$, with values chosen such that hedge providers will apply a discount to the top ten percent of outcomes. We model illiquidity in the financial markets by limiting trade volumes for each contract to 60% of installed capacity for each technology; alternatively, this limit can be seen as a way for the two-stage model to reflect the fact that contracts typically cover only some fraction of a project's life. The value of 60% was chosen to calibrate the level of expected unserved energy in the base case of our model to that of [12], and is binding for all resources in all of our numerical examples. In general, tightening this constraint would lead to greater unserved energy and reduce consumer surplus in equilibrium [26]. Input cost parameters for the six generation technologies in the base case are shown in Table I. Investment costs $\underline{C}_i^{INV}$ and energy costs C_{fg}^{EN} are tuned such that solving (EQ) with the chosen risk and trading parameters results in a mix approximating the present ERCOT system.

In the perfectly competitive, risk-neutral optimization setting of model (OP), investors would add capacity until the expected net revenue of each technology precisely matched the upfront investment cost. In the solution to model (EQ), expected net revenue for technology i, i.e., operating profits before accounting for hedging, can be calculated as $\sum_{f\in\mathcal{F}}\sum_{s\in\mathcal{S}} p_{fs}\pi_{fis}$. Since investors are risk-averse and pay a risk premium on hedging contracts, this value must be greater than the investment cost $\underline{C}_i^{INV}$ used in model (EQ) and implies an estimated weighted average cost of capital (WACC) for the investment. Using this expected net revenue as the investment cost $\hat{C}_i^{INV}$ in model (OP) gives rise to the same capacity mix that results from model (EQ). In other words, we construct the base case such that solving the models (EQ) and (OP) gives nearly identical results, with the cost of capital endogenous in the former and exogenous in the latter.

B. Hypothetical Futures

To assess how risk may evolve in systems heavily reliant on VRE, we modify input cost parameters to reflect technological improvements for solar and wind combined with a higher price for carbon-intensive fuels for the baseload and peaker generators. The cost of storage, which is artificially reduced in the current mix to result in a non-zero installed capacity, is the same in all three cases. In the "high VRE" mix, the investment cost for wind is halved, while that for solar drops 60%. In order to result in a system with consumer surplus roughly equal to that

TABLE I
COST ASSUMPTIONS: CURRENT MIX

Tech i	Investment (Risk-free) $\underline{C}_i^{INV}$ (\$/kW-yr)	Investment (Estimated) $\hat{C}_i^{INV}$ (\$/kW-yr)	Fuel price 1 C_{1i}^{EN} (\$/MWh)	Fuel price 2 C_{2i}^{EN} (\$/MWh)
Baseload	81	110	15	45
Peaker	50	75	30	90
Backup	22	36	900	900
Solar	134	168	0	0
Interior Wind	143	171	0	0
Coastal Wind	141	172	0	0
Storage	17	29	N/A	N/A

TABLE II
COST ASSUMPTIONS: HIGH VRE MIX

Tech i	Investment (Risk-free) $\underline{C}_i^{INV}$ (\$/kW-yr)	Investment (Constant) $\hat{C}_i^{INV}$ (\$/kW-yr)	Fuel price 1 C_{1i}^{EN} (\$/MWh)	Fuel price 2 C_{2i}^{EN} (\$/MWh)
Baseload	81	110	165	195
Peaker	50	75	330	390
Backup	22	36	900	900
Solar	54	68	0	0
Interior Wind	71	85	0	0
Coastal Wind	70	86	0	0
Storage	17	29	N/A	N/A

TABLE III
COST ASSUMPTIONS: EXTREME VRE MIX

Tech i	Investment (Risk-free) $\underline{C}_i^{INV}$ (\$/kW-yr)	Investment (Constant) $\hat{C}_i^{INV}$ (\$/kW-yr)	Fuel price 1 C_{1i}^{EN} (\$/MWh)	Fuel price 2 C_{2i}^{EN} (\$/MWh)
Baseload	81	110	900	900
Peaker	50	75	900	900
Backup	22	36	900	900
Solar	37	47	0	0
Interior Wind	51	61	0	0
Coastal Wind	50	62	0	0
Storage	17	29	N/A	N/A

of the current mix, the energy cost for the baseload resource increases by \$150/MWh in both fuel price scenarios, while the energy cost for the peaker technology increases by \$300/MWh in both fuel price scenarios. In principle, these cost changes can represent either changes in the technologies themselves (e.g., due to learning effects) or changes in government policy (e.g., due to subsidies or a carbon tax). The resulting parameters are summarized in Table II. The "extreme VRE" mix takes this further, reducing the investment cost of wind by 64% and solar by 72% from the base case, while raising the fuel price of the baseload and peaker technologies so high that they are eliminated from the capacity mix. The parameters for the "extreme VRE" mix are shown in Table III. With these scenarios, our intent is not to forecast a likely future but rather to create a stress test for market design reflecting conditions with high shares of variable renewable energy.

C. Outcome Summary

In the solutions resulting from solving (EQ) under the three sets of cost assumptions, variable resources produce 18.6% of energy in the current mix, 96.4% of energy in the high VRE mix, and 99.2% of energy in the extreme VRE mix. If the backup resource is interpreted as demand response, the VRE share in the extreme mix is 100%. In other words, the cost parameters are chosen such that both future mixes have a share of energy coming from variable, zero-marginal cost resources that is well above the share typically found in system optimization models using more realistic projections of technology costs. The future mixes also feature somewhat less storage than found in other macro-energy systems models, relying instead on wind and solar capacities that greatly exceed maximum demand. The installed capacity in equilibrium for the three cases is shown in Table IV.

[illegible] demand response unit;

TABLE IV
INSTALLED CAPACITY IN EQUILIBRIUM SOLUTIONS (MW)

Tech	Current Mix	High VRE Mix	Extreme VRE Mix
Baseload	51,022	19,741	-
Peaker	19,681	6,331	-
Backup	4,874	8,537	25,053
Solar	3,051	52,599	70,446
Interior Wind	10,390	49,558	67,108
Coastal Wind	2,689	50,191	72,684
Storage	12	42,654	90,006

Key outcome measures for the performance of the market are cost, measured as the average price paid for electricity, and

TABLE V
AVERAGE PRICE ($/MWh)

Mix	Constant WACC	Endogenous WACC
Current	51.73	51.73
High VRE	49.60	46.44
Extreme VRE	47.07	45.46

TABLE VI
EXPECTED UNSERVED ENERGY (MWh/yr)

Mix	Constant WACC	Endogenous WACC
Current	4,663	4,661
High VRE	10,377	8,273
Extreme VRE	9,523	17,080

TABLE VII
CHANGE IN CONSUMER SURPLUS RELATIVE TO CURRENT OPTIMUM ($ M/yr)

Mix	Constant WACC	Endogenous WACC
Current	-	-1
High VRE	753	1,979
Extreme VRE	1,724	2,276

reliability, measured as the quantity of non-price-responsive load that must be shed in order to maintain power balance.

We make two observations from Tables V and VI. First, in the high VRE case, the equilibrium solution exhibits both lower cost and higher reliability than the optimum solution. Second, the optimal solution in both the high VRE and extreme VRE cases exhibits much higher levels of unserved energy than is optimal under the current mix. One way to assess the tradeoff between cost and reliability is through the assumed VOLL of $B = \$9,000$/MWh. Annual consumer surplus under each mix can be calculated as

$$CS = \sum_{f\in\mathcal{F}} \sum_{s\in\mathcal{S}} \sum_{t\in\mathcal{T}} p_{fs} L_t \Big((d_t^{fix} + d_t^{res})(B - \lambda_{fst}) - B(d_t^{res})^2/(2D_t^{res}) \Big).$$

We instead report change in consumer surplus, defining the surplus in the optimal solution for the current mix as the baseline. Overall change in surplus is shown in Table VII.

In both the high VRE and extreme VRE mixes, lower prices outweigh the impact of higher unserved energy at the assumed VOLL. Under both sets of assumptions, however, the equilibrium solution yields higher surplus than the solution that assumes a constant cost of capital. This is in direct contrast to the motivating hypothesis for this work: that exposure to risk will be greater in high VRE systems, resulting in a degradation of surplus as market participants are less able to manage risk. The results indicate that, contrary to what may have been expected, overall financial risk in the system actually falls in high VRE scenarios, at least given the parameters and somewhat-stylized equilibrium model assumed herein. We discuss this finding further in the following sections.

TABLE VIII
CONCENTRATION OF SCARCITY EVENTS

	Current	High VRE	Extreme VRE
Number of high-priced hours	216	214	230
Number of years with any high-priced hours	18	16	12
Max # of hours with high prices in 1 year	27	41	58

D. Interannual Revenue Volatility and the Cost of Capital

The προϋπόθεση premise of the equilibrium model is that the cost of capital will change as risk-averse investors and hedge providers respond to the changing distribution of annual revenues. It is widely understood that variable, zero-marginal-cost resources will increase volatility on diurnal, seasonal, and annual timescales. While the findings in Section V-C cannot be considered conclusive given the assumptions required in constructing the model, they suggest that this growth in volatility may not have as significant an effect on interannual timescales, which are likely of greater concern for investors. Here we investigate the changing distribution of net revenues for each technology and the impact on modeled cost of capital. Beyond the assumptions, we note that the model παραλείπει omits broader market factors affecting the cost of capital; accordingly, our emphasis is on a comparison between different sets of technologies with all else equal. Future work could extend and apply this analytical framework to assess the impact of other factors affecting the distribution of annual revenues and market risks, such as the differential impacts of various policy instruments (i.e., subsidies, emissions taxes or limits, etc.) on the cost of capital of different electricity resources.

Overall revenues in energy-only markets depend heavily on times of scarcity, which we define as hours with a price higher than the $900/MWh marginal cost of the backup resource. In our model, such prices can be set either by flexible demand or by involuntary load shedding (e.g., rotating blackouts). Since our model dispatches with perfect foresight within the second stage, it cannot precisely replicate changes in the price distribution that may be expected with significant quantities of storage bidding based on opportunity costs. With that said, since those opportunity costs are likely to depend heavily on the potential for scarcity, the results assume that our simplified representation of the price formation process appropriately describes the distribution of annual revenues.

Table VIII shows how interannual variability in scarcity events increases, with scarcity events becoming more concentrated in certain years in the high and extreme VRE mixes. While the number of scarcity hours across the 36 modeled years does not appreciably change, the number of years with any such events falls from 18 to 12. In conjunction with this drop, while the year with the highest number of scarcity hours in the current mix sees prices above $900/MWh in 27 hours, the equivalent year for the extreme VRE mix has prices above $900/MWh in 58 hours.

Tables IX–XI provide descriptive statistics on the distribution of annual revenues in the equilibrium solutions for the three mixes. We first observe that comparing across the tables confirms

TABLE IX
DISTRIBUTION OF NET REVENUES IN EQUILIBRIUM SOLUTION: CURRENT MIX

	Median ($/kW-yr)	Mean ($/kW-yr)	Std Dev ($/kW-yr)	Skew
Baseload	79	110	83	1.08
Peaker	37	75	79	1.14
Backup	2	36	50	1.28
Solar	175	168	82	0.44
Interior Wind	185	171	81	0.06
Coastal Wind	199	172	81	0.16
Storage	16	29	27	1.19

TABLE X
DISTRIBUTION OF NET REVENUES IN EQUILIBRIUM SOLUTION: HIGH VRE MIX

	Median ($/kW-yr)	Mean ($/kW-yr)	Std Dev ($/kW-yr)	Skew
Baseload	106	113	92	2.13
Peaker	57	76	83	2.48
Backup	0	39	72	2.91
Solar	54	61	21	0.70
Interior Wind	75	77	19	0.46
Coastal Wind	81	79	19	0.22
Storage	21	21	7	0.67

TABLE XI
DISTRIBUTION OF NET REVENUES IN EQUILIBRIUM SOLUTION: EXTREME VRE MIX

	Median ($/kW-yr)	Mean ($/kW-yr)	Std Dev ($/kW-yr)	Skew
Backup	0	44	104	3.31
Solar	45	47	23	0.20
Interior Wind	0	59	20	-0.10
Coastal Wind	60	61	24	0.74
Storage	19	22	9	1.93

the hypothesis that revenue volatility is likely to be greater in VRE-reliant systems: skewness (as well as kurtosis, not shown) grow for most technologies, with the largest increases coming for the baseload, peaker, and backup resources. A second observation is that risk for the renewable resources is inherently lower than that for the other technologies. Because of their low marginal cost, solar and wind are less reliant on rare scarcity events for their revenue. Despite frequent occurrence of prices at $0/MWh, wind and solar resources accrue smaller inframarginal rents on a more regular basis when firm units (including demand response) set the marginal price.

risk-free rate!

WACC before the risk

With additional assumptions on the risk-free rate of return R_f and the length of project life N, the mean net revenue can be used to calculate an implied cost of capital for each technology. With C_i^{INV} as the mean net revenue earned by technology i in equilibrium, the WACC R_m can be found by solving the equation

C_i^{INV} → $/w since to inv. cost?

$$\sum_{n=1}^{N} \frac{C_i^{INV}}{(1+R_m)^n} = \sum_{n=1}^{N} \frac{C_i^{INV}}{(1+R_f)^n}. \tag{9}$$

Table XII shows the WACC implied by the equilibrium solution for each mix assuming a risk-free rate of return of 4% and a 20-year life for all technologies. We note that while this "risk-free" rate is higher than currently observed in many areas, the model excludes many other sources of risk faced by generation projects.

TABLE XII
IMPLIED WEIGHTED AVERAGE COST OF CAPITAL IN EQUILIBRIUM

	Current	High VRE	Extreme VRE
Baseload	7.8%	8.1%	-
Peaker	9.2%	9.4%	-
Backup	10.3%	11.7%	13.7%
Solar	6.7%	5.4%	6.6%
Interior Wind	6.1%	5.0%	5.6%
Coastal Wind	6.4%	5.3%	6.2%
Storage	11.0%	6.6%	6.8%

The implied cost of capital for each technology corresponds to the skewness of its underlying revenue distribution, with the effect that renewable resources see the lowest cost of capital. Recent empirical evidence suggests that this separation is not merely a modeling artifact, but a directionally correct reflection of market outcomes [45]. The magnitude of the difference, however, is more subject to scrutiny, particular given our model's narrow focus. In particular, we note that inclusion of transmission congestion would likely compress this difference, since the best wind and solar resources are often located far from load centers [46].

A more surprising result is that, while the WACC increases for the baseload, peaker, and backup resources when moving from the current mix to the high and extreme VRE cases, it falls for solar, wind, and storage. The increase in cost of capital for the firm resources is consistent with the observation above that high VRE systems increase interannual variability in scarcity periods, which contribute the vast majority of inframarginal rents for these resources. Renewable resources are likewise impacted by this increased variability in scarcity periods. However, wind and solar resources also face reduced exposure to fuel cost uncertainty, as the Peaker and Baseload resources set prices less frequently in the modeled future systems. Fuel costs vary by a factor of three between the two fuel scenarios for these resources, making these random variables the most important source of risk for the zero-marginal-cost resources. It thus appears that reduced exposure to fuel price uncertainty outweighs the increased interannual uncertainty in scarcity pricing periods, resulting in decreased risk overall for wind and solar resources under these assumptions. Given uncertainty about the future course of policies related to carbon emissions in addition to underlying volatility in the price of natural gas, a large range in potential fuel costs may be plausible over the lifetime of new power plants. With that said, a reduction in the spread between fuel price scenarios would decrease the magnitude of the effect shown in Table VII, and the sensitivity of the WACC for all resources to the types of risk considered as well as the specified marginal distributions of uncertain parameters highlights the need for further numerical research on this topic.

E. Reliability and the Revenue Distribution

A distinguishing feature of electricity markets is the presence of a large share of inelastic demand. While it is hoped that the proliferation of connected devices will enable more active demand-side participation, the lack of a clear valuation for electric service during times of scarcity poses a problem for market

TABLE XIII
EFFECT OF THE VALUE OF LOST LOAD ON COST OF CAPITAL

	VOLL = $9,000/MWh	VOLL = $20,000
Baseload	8.1%	8.9%
Peaker	9.4%	10.8%
Backup	11.7%	15.2%
Solar	5.4%	5.1%
Interior Wind	5.0%	4.9%
Coastal Wind	5.3%	5.3%
Storage	6.6%	7.1%

Note: assumes cost parameters from high VRE mix

design. With low levels of price-responsive demand, economic efficiency dictates that demand curtailment or load shedding must occasionally set the market price in order for generators to earn sufficient inframarginal revenues to recover fixed costs. There are significant disagreements as to the appropriate frequency of involuntary loss of load events and, correspondingly, the price systems should be willing to pay to avoid them. For example, while ERCOT uses a VOLL of $9,000/MWh, parameters used in the PJM capacity market imply a VOLL of approximately $700,000/MWh [47].

The results from Table VI demonstrate that debates on the appropriate VOLL could grow in importance over time. As the relative cost of firm and variable resources changes, it becomes optimal to shed larger quantities of firm load in expectation. This increased load shedding occurs despite the significant expansion of the Backup resource, to 25 GW of capacity in the extreme VRE case. The economic and public health consequences of load shedding on this scale in the February 2021 Texas blackouts suggest a marginal VOLL during the event well above the administrative value used in the market. Maintaining current standards for involuntary load shedding implies an increase in the VOLL used to compute prices during times of scarcity. An increase in VOLL, however, has the potential to inject even more volatility into the distribution of net revenue. To illustrate this numerically, we solve model (EQ) using technology costs from the high VRE case, but raising the VOLL from $9,000/MWh to $20,000/MWh, a value sufficient to reduce expected unserved energy from 8,273 to 6,161 MWh/yr in equilibrium (closer to the 4,663 MWh/yr in the Current scenario). The effect of this increase in VOLL on the cost of capital is shown in Table XIII. Cost of capital increases further for firm resources, with the backup resource seeing the largest increase.

more volatility
άρα για τα firms
↑ cost of capital.

VI. CONCLUSION

Εν μέσω προβολών

Amid projections that wind and solar will come to provide a majority of energy in many systems worldwide, operators and regulators of liberalized electricity markets are examining how to guarantee resource adequacy with high levels of variable, zero-marginal-cost resources. In the optimization modeling approach that has become the standard analytical framework for examining power markets, neither variability nor zero marginal cost poses any problem. A key consideration in real-world markets, however, is how market participants will respond to growing price volatility. In systems relying on decentralized investments by market participants, successful market design includes the ability for generators to manage risk through vertical integration, long-term contracts with loads, or bank hedges. In systems counting on centralized long-term market constructs, such as capacity markets or reliability options, a challenge in the design of a resource adequacy mechanism is ensuring that the resulting financial obligations are compatible with the diverse risk profiles of resources in the market. This need for specificity in risk management is potentially in tension with the broader goal of promoting competition between resources.

To help answer these questions, we develop a stochastic equilibrium model in which risk-averse investors are able to trade several resource-specific long-term hedging products with hedge providers to help manage risk. In exploratory numerical tests using data from ERCOT, we confirm that a shift to higher shares of variable and zero-marginal-cost wind and solar resources increases the interannual variability and concentration of scarcity pricing periods responsible for a substantial portion of the intramarginal rents collected by all resources. This shift results in a higher cost of capital for firm resources. However, we observe a lower cost of capital for zero-marginal-cost renewable resources, due to reduced exposure of these resources to fuel price uncertainty, given a sharp decline in the number of hours when fuel-consuming resources set market prices. The net effect of these two changes is that overall investment risk for the system as a whole is lower in the future system with higher shares of wind and solar resources. This finding stands in contrast to commonly-expressed concerns that power systems with high shares of renewables will entail substantial increases in market risk that may make current electricity market designs untenable. However, increased risk for the firm resources contributes to lower reliability in the future systems, suggesting that existing challenges to ensuring resource adequacy will only grow without market adaptations or policy interventions to facilitate long-term risk sharing. Overall, the results highlight the need to understand the evolving distribution of revenues, investor risk attitudes, the role of storage and the demand side in price formation, and the need for multilateral risk sharing in future systems.

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REFERENCES

[1] M. Browning et al., “Net-zero CO2 by 2050 scenarios for the United States in the energy modeling forum 37 study,” *Energy Climate Change*, vol. 4, 2023, Art. no. 100104. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666278723000119

[2] E. Ela, M. Milligan, A. Bloom, A. Botterud, A. Townsend, and T. Levin, “Evolution of wholesale electricity market design with increasing levels of renewable generation,” Nat. Renewable Energy Lab, Golden, CO, USA, Tech. Rep. NREL/TP-5D00-61765, Sep. 2014. [Online]. Available: https://www.nrel.gov/docs/fy14osti/61765.pdf

[3] B. Frew, M. Milligan, G. Brinkman, A. Bloom, K. Clark, and P. Denholm, “Revenue sufficiency and reliability in a zero marginal cost future,” Nat. Renewable Energy Lab, Golden, CO, USA, Tech. Rep. NREL/CP-6A20-66935, Nov. 2016. [Online]. Available: https://www.nrel.gov/docs/fy17osti/66935.pdf

[4] P. Joskow, “Challenges for wholesale electricity markets with intermittent renewable generation at scale: The U.S. experience,” *Oxford Rev. Econ. Policy*, vol. 35, no. 2, pp. 291–331, 2019.

[5] J. Bushnell, M. Flagg, and E. Mansur, “Capacity markets at a crossroads,” Apr. 2017. [Online]. Available: https://sites.hks.harvard.edu/hepg/Papers/2017/WP278Updated.pdf

[6] W. W. Hogan, “Market design practices: Which ones are best? [in my view],” *IEEE Power Energy Mag.*, vol. 17, no. 1, pp. 100–104, Jan./Feb. 2019.

[7] C. Vazquez, M. Rivier, and I. Perez-Arriaga, “A market approach to long-term security of supply,” *IEEE Trans. Power Syst.*, vol. 17, no. 2, pp. 349–357, May 2002.

[8] P. Cramton and S. Stoft, “The convergence of market designs for adequate generating capacity,” Apr. 2006. [Online]. Available: https://dspace.mit.edu/handle/1721.1/45053

[9] F. Schweppe, M. Caramanis, R. Tabors, and R. Bohn, *Spot Pricing of Electricity*, 1st ed. New York, NY, USA: Springer, 1988.

[10] G. Leslie, D. Stern, A. Shanker, and M. Hogan, “Designing electricity markets for high penetrations of zero or low marginal cost intermittent energy sources,” *Elect. J.*, vol. 33, no. 9, 2020, Art. no. 106847, [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1040619020301391

[11] J. Mays, D. Morton, and R. O’Neill, “Asymmetric risk and fuel neutrality in electricity capacity markets,” *Nature Energy*, vol. 4, pp. 948–956, 2019.

[12] S. Newell et al., “Estimation of the market equilibrium and economically optimal reserve margins for the ERCOT region,” 2018. [Online]. Available: http://www.ercot.com/content/wcm/lists/143980/10.12.2018_ERCOT_MERM_Report_Final_Draft.pdf

[13] J. Mays, M. T. Craig, L. Kiesling, J. C. Macey, B. Shaffer, and H. Shu, “Private risk and social resilience in liberalized electricity markets,” *Joule*, vol. 6, no. 2, pp. 369–380, Feb. 2022.

[14] A. D. Mills, T. Levin, R. Wiser, J. Seel, and A. Botterud, “Impacts of variable renewable energy on wholesale markets and generating assets in the United States: A review of expectations and evidence,” *Renewable Sustain. Energy Rev.*, vol. 120, 2020, Art. no. 109670. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032119308755

[15] J. Riesz, I. MacGill, and J. Gilmore, “Examining the viability of energy-only markets with high renewable penetrations,” in *Proc. IEEE PES Gen. Meeting Conf. Expo.*, 2014, pp. 1–5.

[16] P. Joskow, “Competitive electricity markets and investment in new generating capacity,” in *The New Energy Paradigm*, D. Helm, Ed. London, U.K.: Oxford Univ. Press, 2007.

[17] J. Mays, “Missing incentives for flexibility in wholesale electricity markets,” *Energy Policy*, vol. 149, 2021, Art. no. 112010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421520307217

[18] M. Rothkopf, “Dealing with failed deregulation: What would price C. watts do?,” *Electricity J.*, vol. 20, no. 7, pp. 10–16, 2007.

[19] K. Yoo and S. Blumsack, “Can capacity markets be designed by democracy?,” *J. Regulatory Econ.*, vol. 53, no. 2, pp. 127–151, Apr. 2018.

[20] A. Rai and O. Nunn, “On the impact of increasing penetration of variable renewables on electricity spot price extremes in Australia,” *Econ. Anal. Policy*, vol. 67, pp. 67–86, 2020.

[21] D. Newbery, “Missing money and missing markets: Reliability, capacity auctions and interconnectors,” *Energy Policy*, vol. 94, pp. 401–410, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421515301555

[22] J. Riesz, J. Gilmore, and I. MacGill, “Assessing the viability of energy-only markets with 100% renewables,” *Econ. Energy Environ. Policy*, vol. 5, no. 1, pp. 105–130, 2016.

[23] A. Ehrenmann and Y. Smeers, “Generation capacity expansion in a risky environment: A stochastic equilibrium analysis,” *Operations Res.*, vol. 59, no. 6, pp. 1332–1346, 2011, doi: 10.1287/opre.1110.0992.

[24] D. Ralph and Y. Smeers, “Risk trading and endogenous probabilities in investment equilibria,” *SIAM J. Optim.*, vol. 25, pp. 2589–2611, 2015.

[25] A. Philpott, M. Ferris, and R. Wets, “Equilibrium, uncertainty and risk in hydro-thermal electricity systems,” *Math. Program.*, vol. 157, no. 2, pp. 483–513, 2016, doi: 10.1007/s10107-015-0972-4.

[26] G. de M. d’Aertrycke, A. Ehrenmann, and Y. Smeers, “Investment with incomplete markets for risk: The need for long-term contracts,” *Energy Policy*, vol. 105, pp. 571–583, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421517300411

[27] I. Abada, G. de Maere d’Aertrycke, and Y. Smeers, “On the multiplicity of solutions in generation capacity investment models with incomplete markets: A risk-averse stochastic equilibrium approach,” *Math. Program.*, vol. 165, no. 1, pp. 5–69, 2017, doi: 10.1007/s10107-017-1185-9.

[28] O. D. Hart, “Incomplete contracts and the theory of the firm,” *J. Law Econ., Org.*, vol. 4, no. 1, pp. 119–139, 1988.

[29] I. Cheng and W. Xiong, “Financialization of commodity markets,” *Annu. Rev. Financial Econ.*, vol. 6, no. 1, pp. 419–441, 2014, doi: 10.1146/annurev-financial-110613-034432.

[30] F. Billimoria and R. Poudineh, “Market design for resource adequacy: A reliability insurance overlay on energy-only electricity markets,” *Utilities Policy*, vol. 60, no. C., 2019, Art. no. 100935. [Online]. Available: https://EconPapers.repec.org/RePEc:eee:juipol:v:60:y:2019:i:c:15

[31] P. Simshauser, “Merchant utilities and boundaries of the firm: Vertical integration in energy-only markets,” *Cambridge Work. Papers Econ. 2039*, Faculty of Economics, University of Cambridge, 2020.

[32] A. Prabhu, R. Langberg, M. Ferguson, K. Yarborough, S. White, and M. Tsahalis, “Power market update: Knowledge speaks but wisdom listens,” May 2017. [Online]. Available: https://www.spglobal.com/_assets/documents/corporate/mg/Aneesh-Hedging-Paper.PDF

[33] E. Caplan, “Financial arrangements behind new generating capacity,” Oct. 2018. [Online]. Available: https://www.publicpower.org/resource/financial-arrangements-behind-new-generating-capacity

[34] F. Wolak, “An empirical analysis of the impact of hedge contracts on bidding behavior in a competitive electricity,” *Int. Econ. J.*, vol. 14, no. 2, pp. 1–39, 2000.

[35] P. Härtel and M. Korpås, “Demystifying market clearing and price setting effects in low-carbon energy systems,” *Energy Econ.*, vol. 93, 2021, Art. no. 105051. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0140988320303911

[36] D. Böttger and P. Härtel, “On wholesale electricity prices and market values in a carbon-neutral energy system,” *Energy Econ.*, vol. 106, 2022, Art. no. 105709. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0140988321005600

[37] M. B. Anwar et al., “Modeling investment decisions from heterogeneous firms under imperfect information and risk in wholesale electricity markets,” *Appl. Energy*, vol. 306, 2022, Art. no. 117908. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921012198

[38] P. Artzner, F. Delbaen, J. Eber, and D. Heath, “Coherent measures of risk,” *Math. Finance*, vol. 9, no. 3, pp. 203–228, 1999. [Online]. Available: https://EconPapers.repec.org/RePEc:bla:mathfi:v:9:y:1999:i:3:p:203-228

[39] R. Rockafellar and S. Uryasev, “Optimization of conditional value-at-risk,” *J. Risk*, vol. 2, pp. 21–41, 2000.

[40] H. Gérard, V. Leclère, and A. Philpott, “On risk averse competitive equilibrium,” *Operations Res. Lett.*, vol. 46, no. 1, pp. 19–26, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167637717303383

[41] M. M. Rienecker et al., “Merra: Nasa’s modern-era retrospective analysis for research and applications,” *J. Climate*, vol. 24, no. 14, pp. 3624–3648, 2011. [Online]. Available: https://journals.ametsoc.org/view/journals/clim/24/14/jcli-d-11-00015.1.xml

[42] R. Müller, U. Pfeifroth, C. Träger-Chatterjee, J. Trentmann, and R. Cremer, “Digging the meteosat treasure–3 decades of solar surface radiation,” *Remote Sens.*, vol. 7, no. 6, pp. 8067–8101, 2015. [Online]. Available: https://www.mdpi.com/2072-4292/7/6/8067

[43] S. Pfenninger and I. Staffell, “Long-term patterns of European pv output using 30 years of validated hourly reanalysis and satellite data,” *Energy*, vol. 114, pp. 1251–1265, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544216311744

[44] I. Staffell and S. Pfenninger, “Using bias-corrected reanalysis to simulate current and future wind power output,” *Energy*, vol. 114, pp. 1224–1239, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544216311811

[45] K. Kempa, U. Moslener, and O. Schenker, “The cost of debt of renewable and non-renewable energy firms,” *Nature Energy*, vol. 6, pp. 135–142, Jan. 2021, doi: 10.1038/s41560-020-00745-x.

[46] S. Risanger and J. Mays, “Congestion risk, transmission rights, and investment equilibria in electricity markets,” *Energy J.*, vol. 45, no. 1, 2024, doi: 10.5547/01956574.45.1.sris.

[47] S. Murphy, L. Lavin, and J. Apt, “Resource adequacy implications of temperature-dependent electric generator availability,” *Appl. Energy*, vol. 262, 2020, Art. no. 114424. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261919321117