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Asymmetric risk and fuel neutrality in electricity capacity markets

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Supplementary Information for Asymmetric Risk and Fuel Neutrality in Electricity Capacity Markets

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Supplementary Note 1: Capacity Market Implementation Challenges

Efforts to implement capacity obligations and markets have encountered a number of challenges. In an energy-only market, resources are inherently rewarded for their ability to perform during scarcity conditions, respecting all network constraints. Achieving a similar result in an ICAP market requires administrative determinations of the amount, type, and location of capacity needed under a range of operating conditions. Simple definitions have proved insufficient [1]. CAISO, for instance, has introduced a separate requirement for flexible capacity [2], while PJM had to redesign their market after the original summer-focused definition proved inadequate to winter needs [3]. The entry of non-traditional resources makes the task even more difficult. Correct compensation of solar and wind relies on a calculation of how well aligned their output is with peak load events [4]. The challenge for storage, demand response, and efficiency resources is perhaps even greater. While miscalculation of capacity obligations or credits would lead to a different generation mix in equilibrium, such distortions are not the focus of this paper.

Perhaps an even more fundamental challenge is the estimation of consumer preferences, which informs the quantity of capacity to be procured. Economic analyses typically put the value of lost load between \$5,000 and \$15,000/MWh [5]. Instead of working from this economic basis, most resource adequacy standards are based on some version of the "1-in-10 standard," ensuring that interruptions happen only infrequently. These standards imply a much higher value of lost load, reaching over \$200,000/MWh [6]. Accordingly, capacity markets implemented with this higher degree of reliability in mind are likely to procure more capacity than would arise in an energy-only market.

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Supplementary Note 2: Operating Profit Approximations

These approximations assume energy sales in the Day-Ahead Market at the PJM pricing node whenever the LMP is above marginal cost and capacity sales in the Base Residual Auction at the RTO-wide clearing price, both summed over delivery years 2014/15 through 2017/18.

Supplementary Note 3: Two Generator Example

For the experiments, the nominal demand D_t^{fix} and length L_t of time blocks $t \in \mathcal{T}$ are constructed based on the load duration curve of PJM in 2017. Rounding demand in each hour up to the nearest gigawatt, demand ranged from 58 to 146 GW. This results in 89 time blocks, with the length determined by the number of hours with demand in the relevant 1 GW range. Given this choice of $\mathcal{T}$, solving each dispatch problem $(ED)_{frs}$ gives the surplus over a year of operations. The amount of price-responsive demand D_t^{res} is set to 1 GW in every time block. We use values $\underline{v}_c^k = 0$ and $\bar{v}_g^k = 0$, indicating that generators sell contracts to consumers. Unless otherwise specified, the other bounds on trading, $\bar{v}_c^k$ and $\underline{v}_g^k$, are set to a multiple of installed capacity large enough to ensure they are non-binding. Availability $A_{grt} = 0.9$ for both technologies in every time block. The baseload generator takes index $g = 1$ and has investment cost $C_1^{INV} = \$350{,}000/\text{MW}$, while the peaker requires a lower $C_2^{INV} = \$50{,}000/\text{MW}$. Supplementary Tables 1 and 2 show the realizations for fuel prices and demand shifters; each scenario is assumed to have equal probability. These give rise to 100 potential year-long scenarios for the dispatch problem. Construction of the demand scenarios, through the introduction of separate upward and downward demand shocks, as well as the chosen realizations of D_f^- and D_s^+, is done for computational convenience: since we avoid constructing multiple scenarios and time blocks with equal demand, a small change in the capacity mix is less likely to produce a large change in generator profitability.

We consider two contracts: a call option with a strike price of $\lambda^k = \$1{,}000/\text{MWh}$ and a future settling at $\lambda^k = \$50/\text{MWh}$. An alternate way to clear the market in futures, more common in practice, would be to allow this λ^k to fluctuate until the first stage payment satisfies $\phi^k = 0$. We choose to instead fix λ^k in order to incorporate all trades identically in Algorithm 1.

Supplementary Table 1: Scenarios for Fuel Prices ($f \in \mathcal{F}$)

	1	2	3	4	5	6	7	8	9	10
C^{EN}_{f1} (\$/MWh)	10	10	10	10	10	10	10	10	10	10
C^{EN}_{f2} (\$/MWh)	30	35	40	45	50	55	60	65	70	75
D^-_f (GW)	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9

Supplementary Table 2: Scenarios for Demand Shifters ($s \in \mathcal{S}$)

	1	2	3	4	5	6	7	8	9	10
D^+_s (GW)	0.01	1.02	2.03	3.04	4.05	5.06	6.07	7.08	8.09	9.095

Supplementary Note 4: Three Generator Example

The variable generator has an average availability of 37.5 percent over time in each scenario. Availability during the highest demand time blocks is 60 percent of installed capacity in the strongly positive scenario, but 15 percent in the strongly negative scenario. Investment cost (annualised at the risk-free rate) is $C_3^{INV} =$ \$150,000/MW and fuel is \$0/MWh. For this example we increase the peaking technology investment cost C_2^{INV} to \$70,000/MW and use the risk parameters $\alpha = \beta = 0.7$ for all market participants.

Supplementary Note 5: Algorithm Comparison

Relative to Höschle et al. [7], we suggest two potential advantages of our approach. In Höschle et al. [7], a price-setting agent updates prices for energy, capacity, and renewable energy certificates simultaneously. By contrast, in Algorithm 1, ADMM-like updates occur for two low-dimensional variables: the level of installed capacity, and the price of financial contracts. The task of choosing step sizes σ and μ is made easier by the fact that these updates occur separately. The second advantage is an outgrowth of a difference between the two models, namely, our inclusion of a quadratic term in the objective function of the consumer. Instead of an ADMM-like update, the majority of dual variables appearing in the joint problem (EQ), which arise from the dispatch problems, are calculated directly by solving $(ED)_{frs}$ for each scenario. This ensures compatibility between the installed capacity and these prices at each step without the need to tune any algorithm parameters. Making a comparable update would be difficult in Höschle et al. [7] because equilibrium solutions occur at points where multiple optimal solutions are possible for the price-setting agent (see the discussion of characteristic scenarios in Abada et al. [8]).

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