The interaction of wholesale electricity market structures under futures with decarbonization policy goals: a complexity conundrum

Bethany Frew[1*], Muhammad Bashar Anwar[1], Sourabh Dalvi[1], and Adria Brooks[2]

[1]National Renewable Energy Laboratory, Golden, CO 80401, U.S.A.
[2]Department of Energy, Washington, D.C., U.S.A.
[*]Corresponding author: Bethany.Frew@nrel.gov

Keywords: competitive wholesale electricity markets, market design, decarbonization, capacity expansion modeling, production cost modeling, renewable energy

Highlights:

- We used EMIS-AS model to explore various market structures and clean energy targets
- Energy-only markets can achieve same clean energy goals as capacity markets
- ORDC scarcity pricing exhibits substitutional relationship with capacity markets
- Even one well-designed market mechanism can achieve desired clean energy targets
- Capacity/reserve eligibility rules for one technology or product can impact others

Abstract

Competitive wholesale electricity markets can help facilitate energy system decarbonization by incentivizing investments in clean energy technologies that meet evolving system needs. We explore market structure impacts on generator operations and deployment by risk-averse, heterogeneous investor firms using the Electricity Markets and Investment Suite – Agent-based Simulation (EMIS-AS) model. We apply clean energy targets (CETs) of 45%–100% by 2035 considering energy, ancillary services, capacity, and clean energy credit (CEC) products and pricing and eligibility rules. Results highlight a complexity conundrum, whereby finding the "right" market design to achieve decarbonization goals and avoid unintended consequences can be a highly-nuanced, non-incremental challenge. Carefully designed energy-only markets can achieve the same CETs as capacity market structures but with different revenue and profitability outcomes. Operating reserve demand curve-based scarcity pricing can substitute capacity markets for similar deployment outcomes. Carbon pricing alone is most effective at achieving decarbonization levels at low CETs, and CEC markets and carbon pricing are substitutionary at high CETs. Restricting technology participation in capacity and operating reserve markets can impact deployment and operations, even for nonrestricted technologies. Adding an inertia product with fast frequency response yields insufficient provision at high CETs, but work is needed to understand frequency requirements and capabilities.

1. Introduction

The growing momentum behind power system decarbonization efforts—prompted by both policy goals and declining costs of clean energy technologies—has led to numerous studies on the technical challenges of such a transformation (e.g., de Sisternes et al., 2016; Denholm et al., 2021; Jenkins et al., 2018). In areas with competitive wholesale electricity markets, the market design structures and rules present additional challenges for ensuring efficient investment and operations of resources that can supply the necessary set of grid services across numerous timescales to support system reliability as the system evolves.

In the United States, wholesale electricity markets managed by independent system operators (ISOs) or regional transmission operators (RTOs) serve roughly two-thirds of the load (EPRI, 2016). The market design varies by each ISO/RTO. While which designs and products will be most effective in supporting the transition to a decarbonized power system is unclear, the general consensus is market design modifications are needed in every existing ISO/RTO area, both for the existing system and the evolution to future decarbonized fleets (e.g., Ela et al., 2021).

Work exploring market products and rules has included a focus on capacity-based products and capacity remuneration mechanisms, operating reserves (including scarcity pricing and eligibility rules), clean energy products like carbon pricing, and energy price formation rules (Frew et al., 2016, 2021a; Hytowitz et al., 2020; Levin et al., 2019; Levin and Botterud, 2015). All these studies have focused on static system buildouts, where the impact of the market design sensitivities was explored assuming a fixed set of input generators. Only a few studies have explored the role of capacity payments on investment decisions for a single future year (e.g., Kwon et al., 2020, 2018).

The existing analyses have primarily used production cost models (PCMs) that solve for the least-cost unit commitment and dispatch of a predetermined system; these PCMs represent a generic wholesale market clearing process. Other types of models can be used to capture the interactions between wholesale market outcomes (prices and dispatch) and the entry and exit decisions of individual generators. These models generally fall into three categories: (1) traditional central-planner style capacity expansion models (CEMs) or generation expansion planning (GEP) models that account for a limited representation of the market clearing process, (2) complementarity models that co-optimize these components through multilevel structures to yield an equilibrium outcome, and (3) agent-based models (ABMs) that represent the market operations and investment/retirement decisions separately.

CEMs and GEPs have visibility into the full set of decision variables across a predetermined optimization horizon but fail to account for imperfect information and investor-firm-level differences in financing and risk profiles, which can lead to overly optimistic outcomes that implicitly assume cost recovery is guaranteed. Complementarity models are considered ideal for capturing the investment-operations interaction, but their numerous application challenges include no guarantee of existence or uniqueness of equilibria, difficulties in scaling beyond very small systems, and restricted operational representation especially as related to convexity. ABMs are far nimbler in their ability to characterize the various aspects of the system with greater detail (including nonconvexity in the operations and investor firm heterogeneity) but have limited ability to achieve a truly co-optimized or equilibrium solution.

We contribute to the literature by (1) explicitly modeling the feedback effect of market designs on the deployment of different technologies by firm type over multiple years while accounting for risk, uncertainty, and imperfect information using the Electricity Markets and Investment Suite agent-based simulation (EMIS-AS) model, (2) exploring a more extensive set of market design and product options, and (3) applying these quantitative efforts over a more aggressive set of decarbonization policies of 45%–100% clean energy by 2035. Our assessment provides value to market planners, operators, and other stakeholders to understand how various market products and associated pricing and eligibility rules can enable the evolution of the generator fleet to achieve a range of decarbonization goals.

Section 2 briefly describes the EMIS-AS model, the test system used for the analysis, the additional model enhancements made to support the wide range of market design sensitivities explored, and the scenario design to explore those dimensions. Section 3 presents and discusses six key findings from our analysis, including market design considerations associated with each finding. Section 4 provides a summary and concluding remarks on policy implications and future work.

2. Methodology

We use EMIS-AS in a vetted test system to systematically explore a diverse set of market structures to understand the interactions between those design options on both operations and deployment under clean energy targets. Here we briefly summarize our methods, model features, and scenarios. See the Supplemental Information (SI) for details.

2.1 EMIS-AS model for investment and market clearing outcomes

This analysis uses the EMIS-AS tool (Figure 1), which is an ABM for exploring investment decisions made by heterogenous, profit-seeking investor agents with different financial characteristics, technology preferences, and risk profiles under uncertainty (Anwar et al., 2022, 2020). ABMs like EMIS-AS are particularly well suited to capture the complex, nonconvex, imperfect interactions between a set of investor firms and wholesale electricity markets over many years or decades. EMIS-AS is superior to other ABMs that focus on generation expansion planning (e.g., Barazza and Strachan, 2020; Botterud et al., 2007; Chappin et al., 2017; Chen et al., 2018; Kell et al., 2019; Kraan et al., 2018; Reeg et al., 2017; Tao et al., 2021) for its ability to capture investor heterogeneity, update investors' forecast parameters using Kalman filters, predict future market prices through an endogenous generation expansion model, and accommodate a customizable representation of wholesale electricity market products.

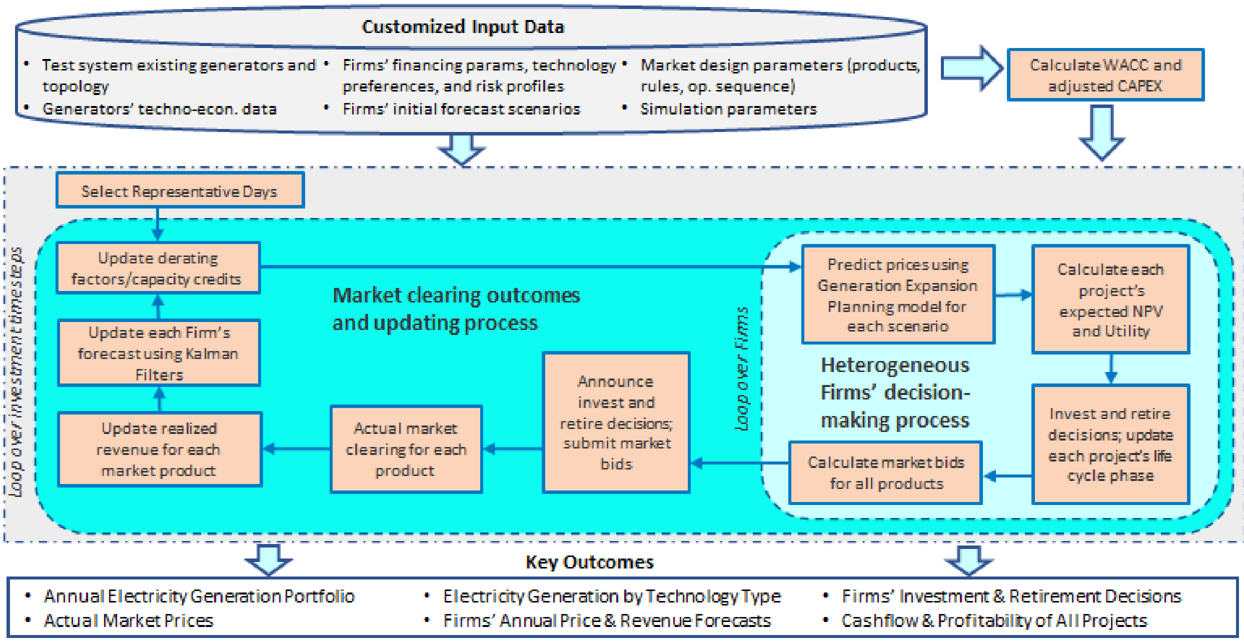

Figure 1. High-level summary of EMIS-AS framework adapted from our previous work (Anwar et al., 2022, 2020).

To enable exploration across various market products and technology characterizations for this analysis, we modified EMIS-AS by:

- increasing to a set of six operating reserve products to cover a wider range of response times (Regulation Up and Down, Flexibility Up and Down, Synchronous, and Primary reserves);
- adding the option for operating reserve demand curves (ORDC) as an alternate scarcity pricing mechanism to the default static scarcity value for Synchronous and Primary reserves;
- adding a stylized inertia product to capture the need for maintaining stable frequency;
- adding a new renewable energy combustion turbine (RE-CT) generator technology, which serves as a generic flexible combustion turbine (CT) generator that is fueled by a range of potential renewable fuels, but with no modeled utilization of variable renewable energy (VRE) curtailed energy for these fuels;
- improving the capacity credit calculation methodology for wind, solar, and storage using an hourly approach;
- adding exogenously-defined carbon pricing; and
- implementing the restriction of some technologies from participating in the forward capacity market and operating reserve markets.

See the SI for details about each of the above items, the EMIS model structure, and the full set of market products.

2.2 Modified RTS-GMLC test system

We apply EMIS-AS to a modified version of a realistic and well-vetted test system with zero-marginal cost wind, utility-scale solar photovoltaic (hereafter referred to as solar), and battery storage across three zones with a total initial derated (unforced) capacity of about 8.4 GW, as shown by zone in Figure 2. Each zone has a separate load profile, load growth, and generator fleet, with transmission flows enforced only across zonal boundaries; fuel prices are assumed consistent across zones. The system was modified from the IEEE Reliability Test System (RTS-GMLC) (Barrows et al., 2019), as documented in (Anwar et al., 2022, 2020). We include a stylized set of four investor firms: New Entrant, Independent Power Producer (IPP), Commercial and Industrial (C&I) IPP, and Large Utility. These firms differ in their size, expectations for the future (in this case applied to load growth), how confident they are in those expectations, their technology preferences, their perceived riskiness (as viewed by a lender and reflected in their discount rates) which impacts their financing parameters, and their risk profiles. Investment technology options include wind, solar, gas CC, gas CT, RE-CT, and battery storage. See the SI for details on all model inputs, including the test system, investor firms, cost assumptions, operating reserve requirements, and time series data.

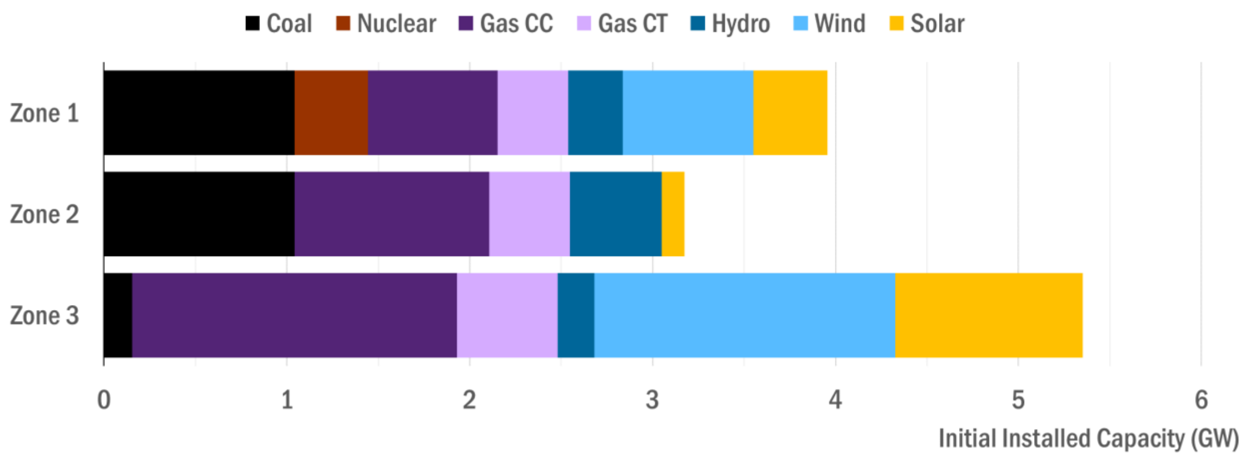

Figure 2. Initial total system-wide installed capacity in 2021 for the modified RTS-GMLC test system used in this analysis.

2.3 Scenarios to explore market design structures across various clean energy targets

We analyze a suite of stylized scenarios to explore different combinations of market products (e.g., the so-called "energy-only" structure versus a structure that includes a forward capacity market), as well as scarcity pricing and eligibility or accreditation rules for operating reserve and capacity markets. These market products and rules capture the generalized nature of many existing or proposed options in U.S. ISOs/RTOs (Sun et al., 2021) through a simplified representation. Because our scenarios apply a bookend-style structure to provide high-level insights into the qualitative trends of these market design considerations, results are not specific to any actual system, and work is needed to explore a more diverse set of system configurations.

We implement a "pyramid" structure to organize our scenarios across different groups of market design combinations, as shown in the colored layers in Figure 3 and Table 1. Our Base scenario assumes energy, capacity, clean energy credit (CEC), and the full set of six operating reserve oroducts, without adding the ORDC scarcity pricing mechanism or a carbon tax. Additional sensitivities explore the application of ORDCs to Primary and Synchronous operating reserves, a carbon tax, higher/lower ORDC scarcity pricing levels, and various sensitivities to evaluate the impact of and to inverter-based resources (IBRs), which include wind, solar, and batteries in this study. The latter includes higher/lower capacity credit assignments, eligibility in capacity markets (as a proxy for price-floor offer rules, like the minimum offer price rule (MOPR), that can effectively preclude these resources from clearing in the capacity market), operating reserve eligibility rules, and the addition of an inertia product. We also include a comparison of the Base scenario (which assumes heterogenous financing, risk, and expectation parameters across the investor firms) with a scenario assuming homogenous firms in the SI.

We orient this analysis to decarbonization policy goals by applying our suite of market design sensitivities to three clean energy targets (CETs) by 2035: 45% (low), 75% (mid), and 100% (high). In each case, we assume a 30% CET in our starting year of 2021 and a linear increase in the annual CET to achieve the desired 2035 target (i.e., 1%/year to reach 45%, 3%/year to reach 75%, and 4.67%/year to reach 100% by 2035). The 30% CET starting point was arbitrarily chosen to be slightly larger than the clean energy level of the starting system. We assume clean energy includes generation from wind, solar, hydropower, nuclear, and RE-CTs. The resulting suite of scenarios includes 17 cases at each CET level, or 51 total scenarios.

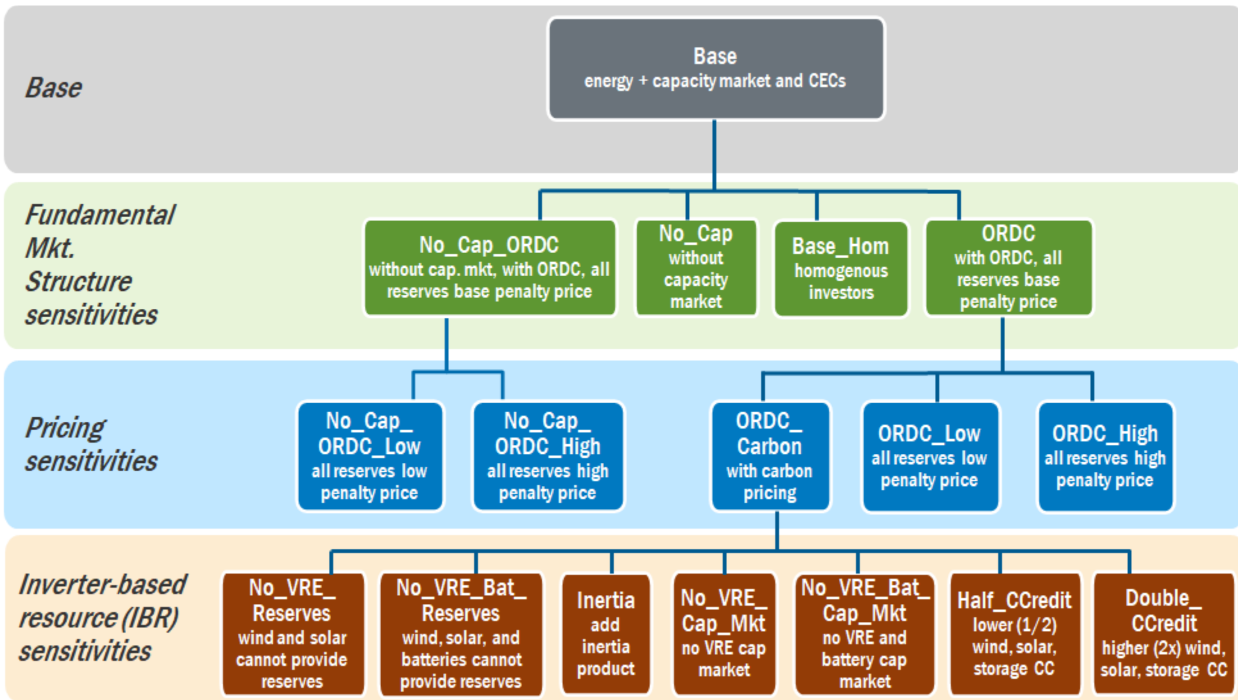

Figure 3. Scenario "pyramid" with the 17 market design scenarios explored for each CET, resulting in 51 total scenarios.

Table 1. Scenario names and parameters from Figure 3.

Category	Scenario Name	Parameters (relative to Base)
Base	Base	Co-optimize energy and operating reserves, variable renewable energy (VRE) and storage provide operating reserves, static and base operating reserve scarcity pricing, CEC product, forward capacity market with default VRE and storage capacity credit and full eligibility, no carbon pricing, investor firm-level heterogeneity and uncertainty, uncertainty only from load growth
Fund. Mkt. Structure	No_Cap_ORDC	No capacity market, add ORDC scarcity pricing for Synchronous and Primary
	No_Cap	No capacity market
	Base_Hom	Homogeneous investor firms
	ORDC	Add ORDC scarcity pricing for Synchronous and Primary
Pricing Sensitivities	No_Cap_ORDC_Low	No capacity market, add ORDC scarcity pricing for Synchronous and Primary, apply low price penalty for all operating reserves (ORDC for Synchronous and Primary, static for others)
	No_Cap_ORDC_High	No capacity market, add ORDC scarcity pricing for Synchronous and Primary, apply high price penalty for all operating reserves (ORDC for Synchronous and Primary, static for others)
	ORDC_Carbon	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing
	ORDC_Low	Add ORDC scarcity pricing for Synchronous and Primary, apply low price penalty for all operating reserves (ORDC for Synchronous and Primary, static for others)
	ORDC_High	Add ORDC scarcity pricing for Synchronous and Primary, apply high price penalty for all operating reserves (ORDC for Synchronous and Primary, static for others)
IBR Sensitivities	No_VRE_Reserves	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing, wind and solar not eligible to provide operating reserves
	No_VRE_Bat_Reserves	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing, wind, solar, and batteries not eligible to provide operating reserves
	Inertia	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing, add inertia product
	No_VRE_Cap_Mkt	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing, wind and solar not eligible to clear capacity market
	No_VRE_Bat_Cap_Mkt	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing, wind, solar, and storage not eligible to clear capacity market
	Half_CCredit	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing, apply 50% of calculated credit for wind, solar, and storage in capacity market eligibility
	Double_CCredit	Add ORDC scarcity pricing for Synchronous and Primary, add carbon pricing, apply 200% of calculated credit for wind, solar, and storage in capacity market eligibility

3. Results

We analyzed the EMIS-AS results for each scenario for investment and retirement decisions, operational outcomes, total costs, market revenues, and firm-level profitability trends. Here we highlight key impacts and differences from the wide range of market structures explored in this analysis. We first provide a high-level contextualization of our findings, followed by an overview of the Base scenario results as a point of reference. We then discuss in detail a set of six key findings using relevant subsets of scenarios to illustrate each point. The full set of results across all scenarios are presented in the SI.

The overarching theme of our results is a complexity conundrum, whereby finding the "right" market design to achieve decarbonization goals can be a highly-nuanced, non-incremental challenge. Layering numerous market products and/or rules can sometimes significantly increase complexity without providing additional benefit to the grid physics, economics, or policy goals. We observe possible substitutionary roles between certain market products, suggesting that only one well-designed option is needed. Furthermore, because of the interconnected nature of markets with operations and investment outcomes, certain combinations of products can yield non-intuitive outcomes, indicating the need to thoroughly evaluate any potential new market design for unintended consequences.

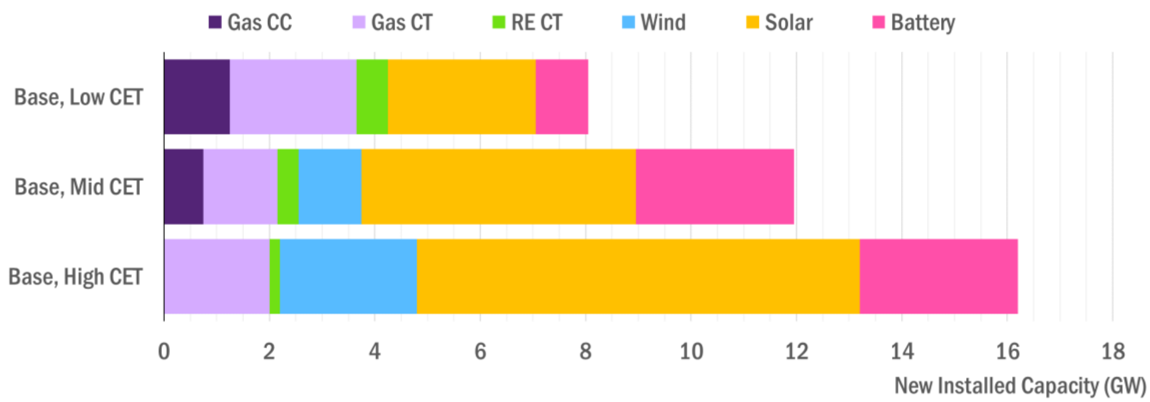

Figure 4. Total new capacity added during the simulation for the Base scenario for the low (45%), mid (75%), and high (100%) CET levels.

As a starting point, in Figure 4 we show the total new capacity added in the system by the final solve year (i.e., 2035) for each CET level (45%, 75%, and 100%) in the Base scenario. These capacities are the new investments during the simulation and do not include the starting point capacities. In EMIS-AS, each firm's decision to invest in new projects depends on the firm's financial parameters and each project's own economics, and it is unaffected by the profitability of the firm's existing total portfolio. Figure 4 shows progressively more deployment of wind, solar, and battery resources as the CET level increases, with a noticeable reduction in gas CC generators and very little change in peaking resources (i.e., gas CT and RE-CT). These trends are also observed in the generation outcomes (see Figure 5), with increasing VRE curtailment at higher CET levels. Also, the total capacity added to the system noticeably increases with higher CETs because of the need for more VRE and storage to meet higher CET targets and the diminishing capacity contribution (i.e., capacity credit) of those resources.

We note an important caveat for our generation results, such as those shown in Figure 5: because the CETs in EMIS-AS are enforced only as capacity procurement standards, some of the generation outcomes do not meet the yearly CET values. For example, in the 100% CET scenario in Figure 5, there is still noticeable gas-fired generation in 2035 when the system is slated to achieve 100% clean-energy-based generation. In this case, gas-fired units are committed—and then run mostly at their minimum generation levels—to meet operating reserve requirements and avoid otherwise incurring scarcity pricing as part of the least-cost market operations solution. We discuss this caveat, including future work to remedy it and market design implications, in the SI.

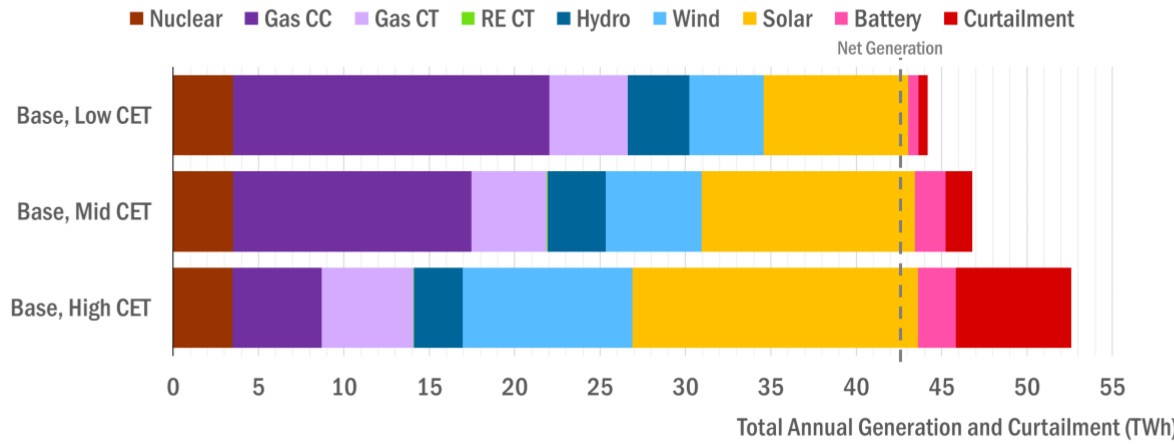

Figure 5. Final solve year (i.e., 2035) total annual generation and curtailment for the Base scenario at 45%, 75%, and 100% CET levels. The net generation output corresponds to the total system demand without battery charging. While the total annual generation differs between the CET levels due to battery charging and losses, the net generation is the same for each CET level.

A comparison of the capacity outcomes for different CET cases at the same clean energy percentage level highlights the importance of the system starting point and policy timeline on generator portfolio evolution and ending point. For example, Figure 6 compares the total installed capacities for the Base scenario Mid and High CET cases at the 75% clean energy level, which occurs in 2035 in the Mid CET case and in 2030 for the High CET case. We see slightly higher installed solar capacity, yet lower battery capacity and higher coal capacity, in the High CET case. This is primarily because some existing coal units have not reached their end of lifetime by 2030 and remain economically viable, which impacts other investment decisions.

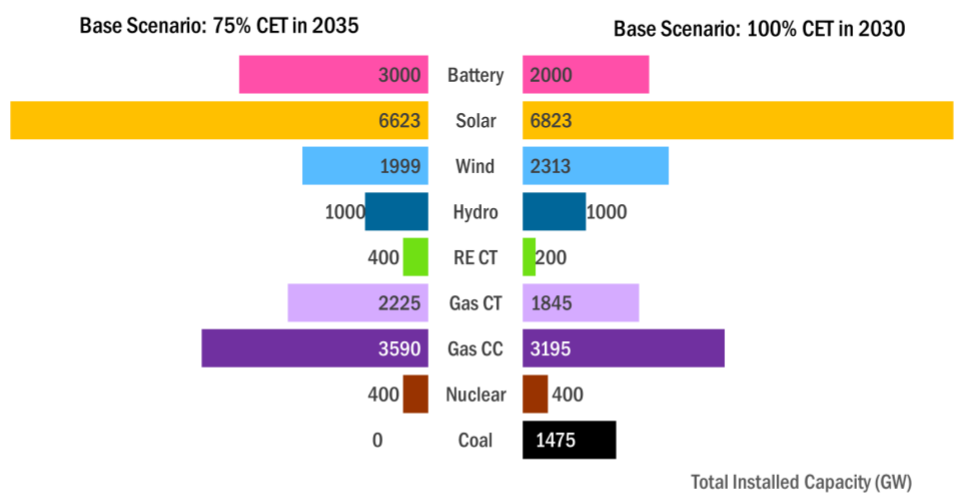

Figure 6. Comparison of total installed capacities for the Mid and High CET cases at 75% clean energy level (which corresponds to years 2035 and 2030 in the Mid CET and High CET cases respectively).

Figure 7 shows the profitability distribution across investor types in the Base scenario for different CET levels. Refer to Section 2.2 and the SI for details on the investor firm financing, risk, and technology investment eligibility assumptions. The Large Utility sees the highest overall investment and associated profitability, as it has the most favorable financing parameters. Similarly, the New Entrant typically has the lowest profitability because of higher cost of capital and limited resources. Also, the profitability of firms that can invest in VRE technologies (i.e., the New Entrant, C&I IPP and the Large Utility) increases with higher CETs, primarily because of significantly higher CEC market revenues. Conversely, the IPP profitability declines with higher CETs, as it can only invest in thermal generation technologies.

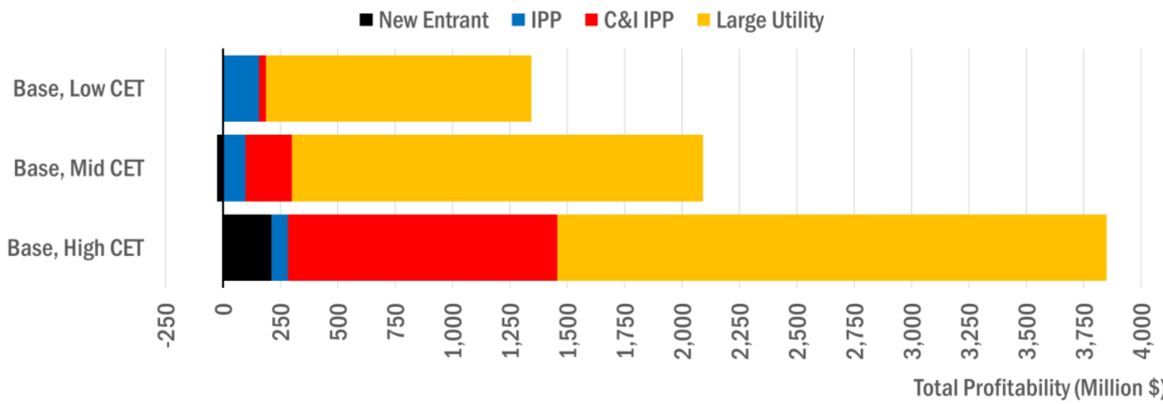

Figure 7. Profitability for new investments across the 15-year simulation horizon in the Base scenario for the 45%, 75%, and 100% CET levels.

As we move from these Base cases down the scenario pyramid, we observe six high-level findings, which we describe in the following subsections. Overall, we find a mixture of distinct trends from individual market design options and highly nuanced interactions of multiple market structures. Though we present high-level takeaways, we caution that these findings might not extend to all power systems because of the differences in underlying resource availability, existing market design, and regional policy factors, among other differentiators. Future work could continue to explore the impact of various market structures on investment and reliability across a wider set of systems and futures.

3.1 Key Finding 1: A carefully designed energy-only market structure can achieve the same system-wide clean energy goals as a capacity market but with different investor-level profitability outcomes and noticeably reduced peaking generation capacity.

We find that a well-designed energy-only market (No_Cap) can achieve the same clean energy goals as an energy-plus-capacity market (Base) without overbuilding nameplate capacity, as shown in Figure 8 and Figure 9. An energy-only market sees similar amounts of total clean energy generation at higher CET levels but with different ratios of wind and solar. The energy-only market also sees a noticeable shift from gas CT to less carbon-intensive gas CC capacity and generation, which is driven by the strong contribution of capacity payments to peaking plant revenues. This aligns with previous work that identified an implicit bias of capacity markets toward high operating cost resources, such as peaking generators (Mays et al., 2019).

We note that these results do not necessarily guarantee sufficient firm capacity for extreme events. Future work could explore the impact of extreme weather or other stressful conditions, such as those resulting in common-mode generator or transmission outages or fuel shortages, to assess the robustness of market strutures in achieving both clean energy and reliability goals.

Additionally, battery capacity is also reduced in the energy-only scenario for Low and Mid CET scenarios, which then suppresses the deployment of solar capacity while increasing wind capacity to meet the CET. This tight coupling of solar and battery, which we observe throughout this study and has been documented in other work (e.g., Cole et al., 2018; Frew et al., 2021b, 2019; Haegel et al., 2017), is because solar's consistent diurnal profiles make it more amenable for intraday storage charging and discharging. Thus, when battery capacity increases, investing in solar—rather than wind—is more economical. More wind deployment (with reduction of battery capacity) leads to noticeably greater renewable energy curtailment absent a capacity market.

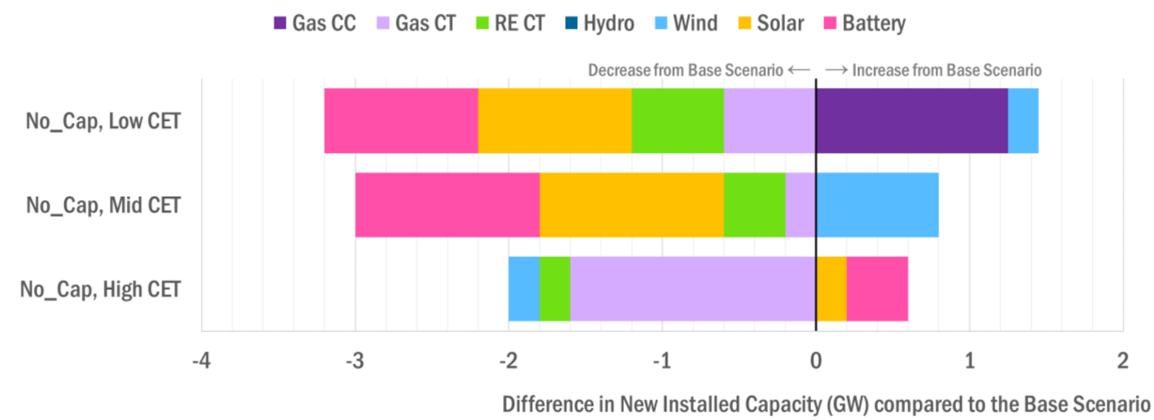

Figure 8. Difference in new capacity added during the simulation compared to the Base scenario (for the respective CET levels shown in Figure 4) for the No_Cap scenario (i.e., energy-only market) for each CET level.

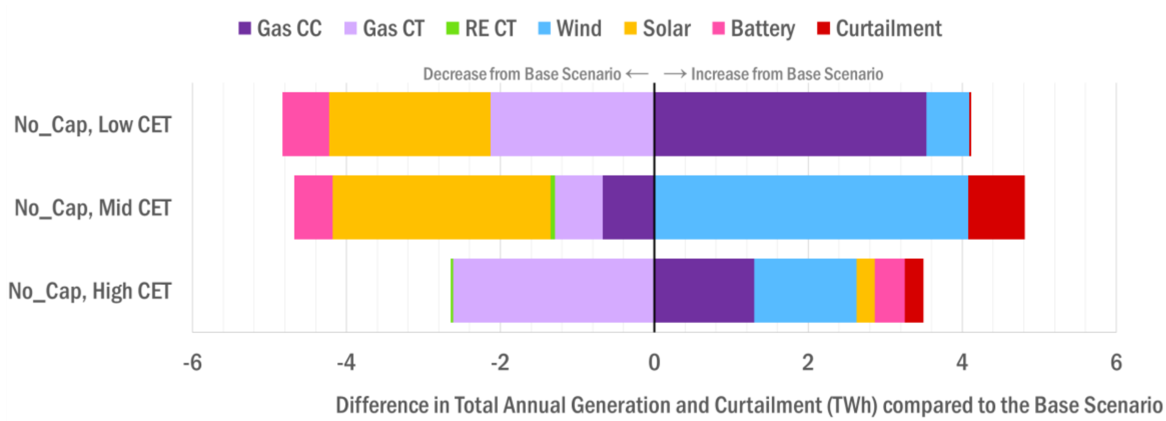

Figure 9. Difference in total 2035 system-wide annual generation and curtailment compared to the Base scenario (for the respective CET levels shown in Figure 5) for the No_Cap (i.e., energy-only market) scenario for each CET level.

Total system costs summed across the 15-year simulation horizon are presented in Figure 10, where we see that greater investment in the capacity market (Base) scenario leads to higher investment and operation and maintenance costs, while fuel and other operational costs remain comparable. Larger CET levels also yield higher total start-up costs, yielding about a 60% increase between the Low and High CET cases for the Base scenario, which is driven by the need for system flexibility, including more cycling-induced starts and stops, introduced by the VRE resources.

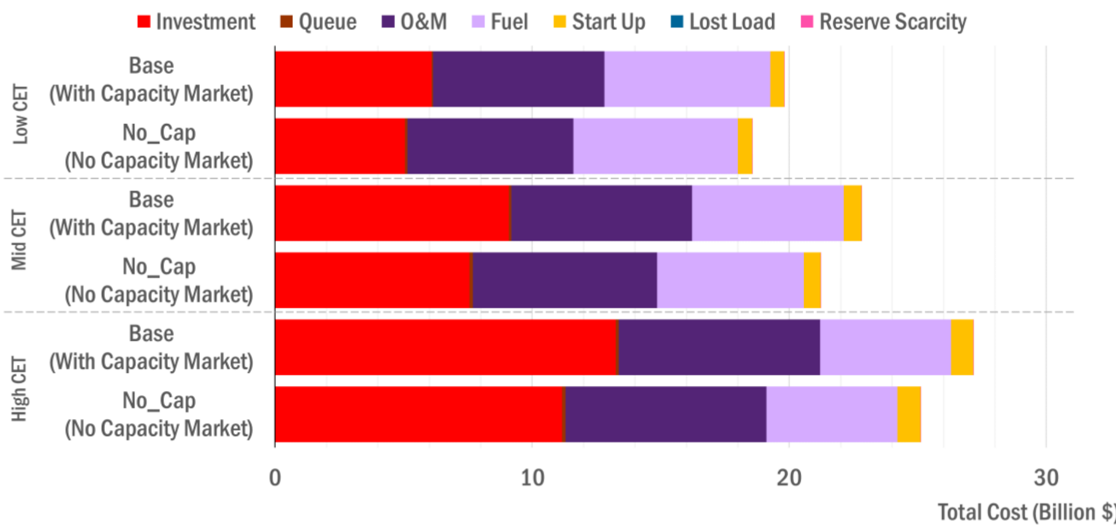

Figure 10. Total system-wide costs for the 15-year simulation horizon for the Base (with capacity market) and No_Cap (without capacity market) scenarios for each CET level.

Absence of capacity markets has noticeable impacts on not only the total market revenues but also the distribution across market products (Figure 11). Generally, the No_Cap scenarios have lower total revenues because of the absence of capacity market revenues. Energy and CEC revenues are noticeably higher in the No_Cap case because of more frequent scarcity pricing and higher CEC market bids, respectively. While these higher revenues cannot entirely compensate for the loss of capacity market revenues, the gap between the No_Cap and Base scenario narrows with higher CET levels primarily because of higher CEC revenues. The average capacity market revenues (comprising about 50% of the total revenues) in Figure 11 are consistent with other markets modeling work (Peter Cramton et al., 2021) but are noticeably larger than the 1%–20% historically observed in actual ISOs/RTOs (EPRI, 2016). This is because (1) capacity scarcity in early simulation years drives large capacity prices, (2) results reflect different future load and portfolio configurations with larger value for new capacity, and (3) lower energy and reserve revenues trigger higher capacity market bids and clearing prices. This reflects a broader trend seen in subsequent sections where the presence of certain pricing mechanisms shifts the relative prominence of capacity and energy revenues. Also, while many details are involved in retail rate design, the lower market revenues seen in the energy-only market (Base) scenario could result in lower costs passed on to electricity ratepayers, assuming each case has the same reliability level; future work could explore this impact.

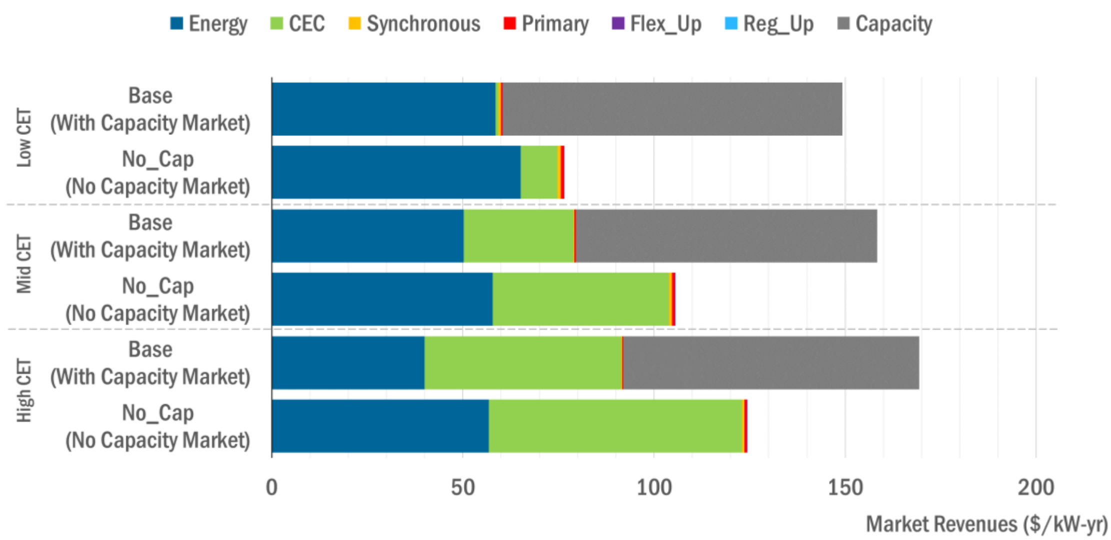

Figure 11. Annual market revenues normalized by the installed capacity and averaged across the 15 simulation years for the Base scenario (energy plus capacity market) versus No_Cap scenario (energy-only market) for each CET level.

These differences in revenue distributions translate into different profitability outcomes for investor firms (Figure 12). Firms that invest in thermal units (IPP and Large Utility) experience reductions in profitability absent a capacity market. Conversely, the New Entrant and C&I IPP experience slight improvements in profitability, as they can more than recover lost capacity market revenues (which already are limited because of low VRE capacity credits) through higher CEC and energy revenues.

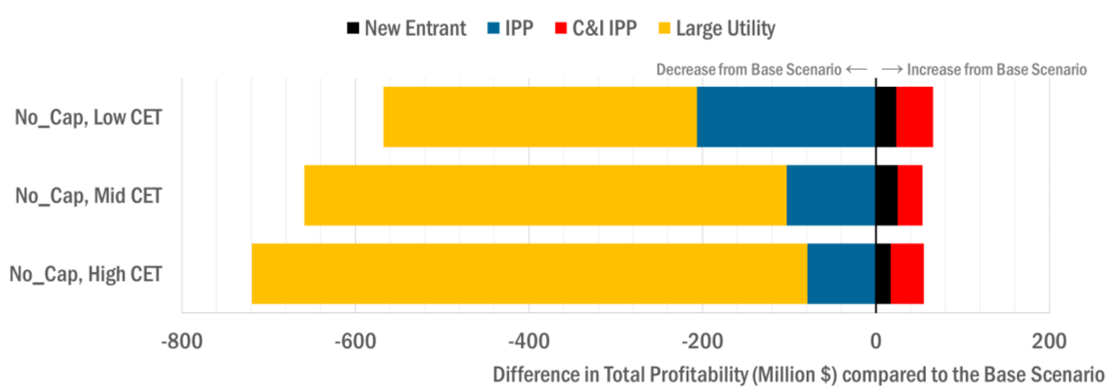

Figure 12. Difference in firms' profitability for new investments (total across the 15-year simulation horizon) compared to the Base Scenario (for the respective CET levels shown in Figure 5) for the No_Cap scenario (energy-only market) for each CET level.

Market Considerations: Carefully designed energy-only markets can achieve clean energy policies with lower system-wide total costs and revenues—and complexity—than similar designs that include a forward capacity market. However, work is needed to better understand whether and how these market structures could most benefit ratepayers, as well as their reliability performance across a wider set of timescales and conditions (e.g., resource adequacy, power flow, extreme weather) to ensure investment in resources to support reliable operations. Results also reveal tradeoffs in generator capacity and utilization between energy-only and capacity market structures, namely with energy-only seeing more wind generation, less gas CT generation, and more VRE curtailment. This indicates that, even while energy-only and capacity market designs can both achieve similar clean energy goals, they must be carefully designed to maximize market efficiency and avoid unintended biases toward or against certain technologies. It also indicates that different investor types may need to reconsider their investment strategies to best position themselves for maximum profitability for the given market structure.

3.2 Key Finding 2: Scarcity pricing mechanisms for operating reserves could strongly favor the deployment and profitability of flexible resources and serve a substitutionary role with capacity remuneration mechanisms.

Our second key finding focuses on the impacts of ORDC scarcity pricing on generator portfolios, revenue distributions, and profitability outcomes. ORDCs trigger higher energy and operating reserve prices that incentivize for available capacity when the system fails to meet its operating reserve requirement (e.g., a shortage or scarcity event). This short-term pricing mechanism helps signal long-term investments that support reliable operations.

Figure 13 depicts the impacts of ORDC and its assumed penalty price on the distribution of market revenues. Adding an ORDC scarcity pricing mechanism (instead of the default static scarcity prices for operating reserves – see SI) significantly reduces capacity market prices and revenues, especially with higher ORDC penalty prices. This is because energy and operating reserve markets are co-optimized, so that an increase in ORDC-induced operating reserve prices and revenues also increases energy market prices and revenues, as shown in Figure 13 for all ORDC scenarios relative to the Base scenario. These larger revenues reduce the going-forward cost for generators, thereby suppressing capacity market bids and associated cleared capacity market price and revenues (see SI for model details). Despite the smaller capacity market revenues with an ORDC, the larger energy and operating reserve revenues result in a net increase in revenues.

Furthermore, we also observe a potential substitutionary relationship between ORDC and capacity market structures. This is based on the tradeoff between high energy and operating reserve prices and no/low capacity market prices. With an ORDC alone (i.e., no capacity market), energy, operating reserve, and CEC revenues are all larger than the case with both a capacity market and ORDC (compare No_Cap_ORDC to the ORDC scenario in Figure 13). However, these increased revenues are insufficient to completely compensate for the absence of capacity market revenues. Conversely—and perhaps most importantly—a capacity market alone (Base scenario) yields similar but slightly greater total revenues as the ORDC only case (No_Cap_ORDC scenario). Though the 75% CET case is shown here, similar substitutional effects were observed for other CET levels (see SI).

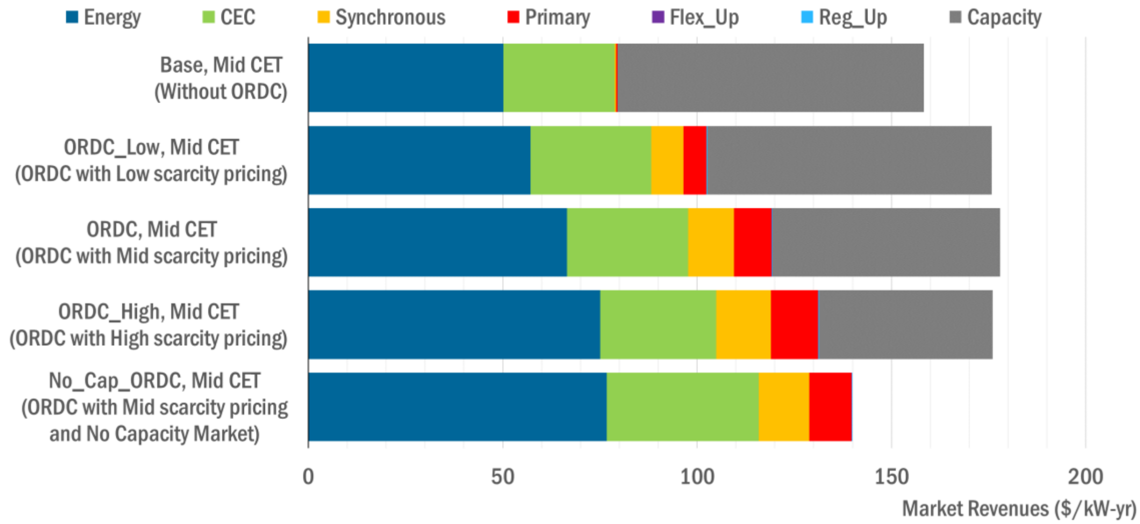

Figure 13. Annual market revenues (averaged across the 15-year simulation horizon) for the Base scenario (which has a capacity market but not ORDCs) versus the corresponding scenarios with ORDCs (with different penalty prices) and the No_Cap_ORDC scenario (which has ORDCs but not a capacity market) for the 75% CET level.

These revenue distribution outcomes have noticeable impacts on the deployment of different technologies, as depicted in Figure 14. Relative to the Base scenario with only a capacity market, the scenarios with only an ORDC and with both a capacity market and ORDC see greater investments in flexible generation technologies, particularly gas CTs, with a notable displacement of solar that is countered by an increase in wind deployment to meet the CET levels. While this trend is stronger for the combined ORDC and capacity market scenario than the scenario with only an ORDC, it indicates that an ORDC pricing mechanism alone (No_Cap_ORDC scenario) is more favorable for flexible resources than a capacity market alone (Base scenario). Future work could explore whether the ORDC only scenario achieves the necessary levels of flexible generator capacity to support resource adequacy as when combined with capacity markets. For the Mid CET level example shown here, gas CT is most favored flexible resource, but at the High CET level (see SI), batteries also see greater deployment, with no change in RE-CT deployment.

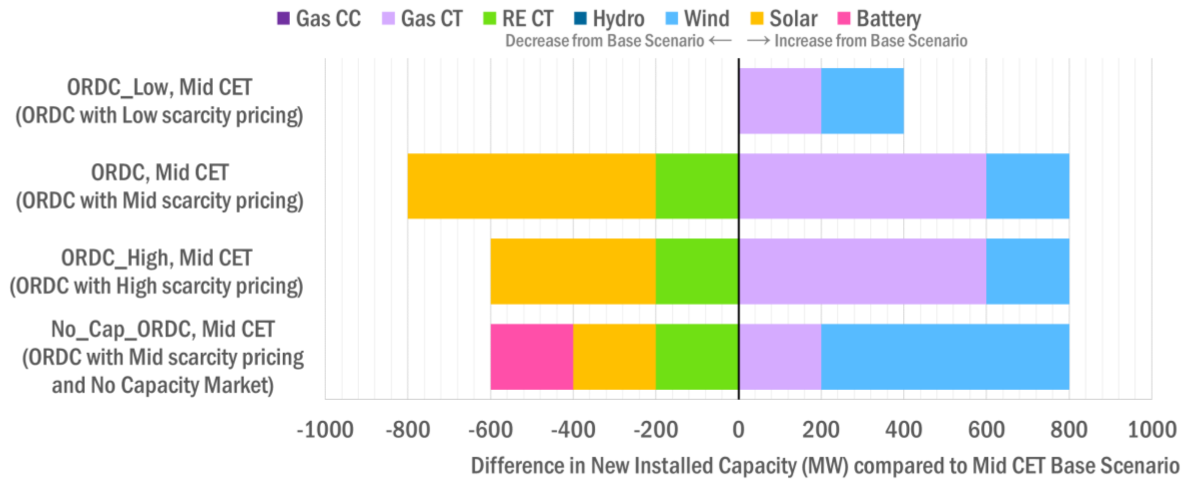

Figure 14. Difference in new capacity added during the simulation for the Base scenario (which has a capacity market but not ORDCs) versus the corresponding scenarios with ORDCs (with different penalty prices) and the No_Cap_ORDC scenario (which has ORDCs but not a capacity market) for the 75% CET level.

Generation results follow a similar trend, as shown for three days from July 8–10 in the final year of the simulation (i.e., 2035) for the Mid CET level in Figure 15. Compared to the case with only a capacity market (Base scenario), the combination of a capacity market and ORDC (ORDC scenario) results in 85% more gas CT generation, 44% more battery generation (i.e., discharge), 5% more wind generation, 9% less gas CC generation, 16% less solar generation, and over 23x increase in curtailment. Over the course of the full year, this ORDC scenario has about 3.2x more curtailment than the Base scenario. Curtailment is larger with the ORDC because more resources, especially flexible generators like gas CTs, must be kept online to avoid scarcity pricing; this reduces the utilization of avialble VRE generation.

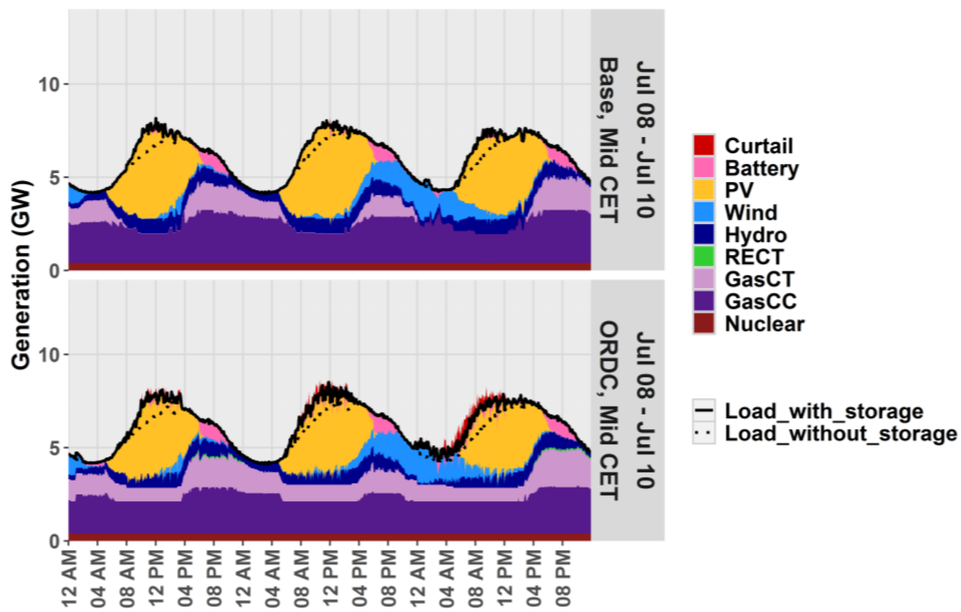

Figure 15. Example of dispatch outcomes for the Base and ORDC scenarios at Mid CET Level in the final simulation year (i.e., 2035).

The addition of ORDCs also has implications for profitability of different firms, as shown in Figure 16. Firms that invest in gas CT technologies (i.e., the IPP and Large Utility) see a significant improvement in profitability due to the addition of ORDCs and corresponding increase in penalty prices. However, the ORDC alone typically leads to reduced profitability for firms which only invest in thermal generation capacity (i.e., the IPP) but higher profitability for the firms with large capacities of variable renewables (i.e., the C&I IPP and Large Utility) primarily because of increased CEC and energy market revenues.

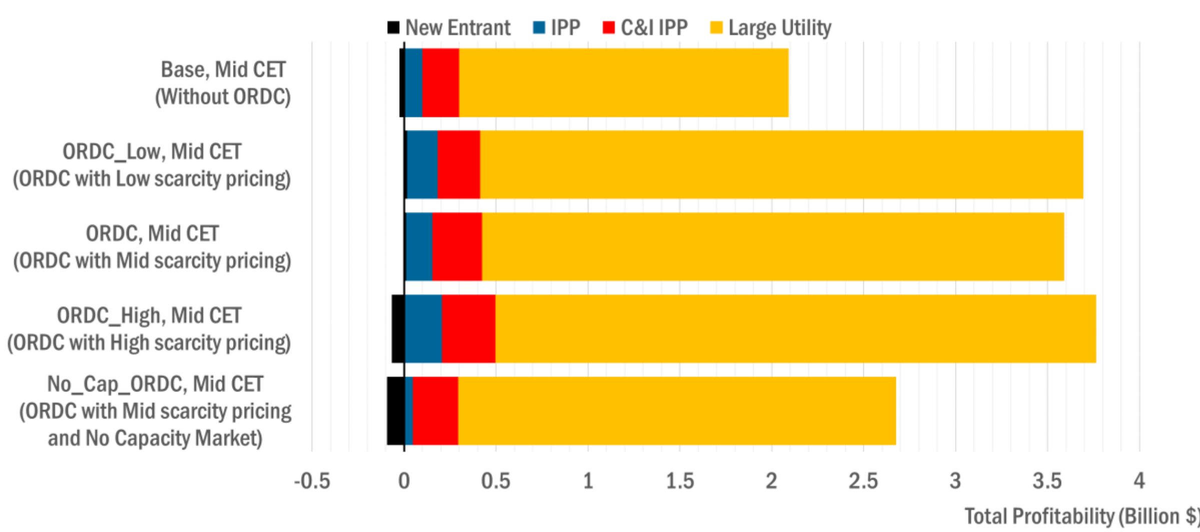

Figure 16. Total investor agent-level profitability (across the 15-year simulation horizon) for the Base scenario (which has a capacity market but not ORDCs) versus the corresponding scenarios with ORDCs (with different penalty prices) and the No_Cap_ORDC scenario (which has ORDCs but not a capacity market) for the 75% CET level.

Market considerations: The results in this section highlight how operating reserve scarcity pricing rules can significantly impact both investments and the market clearing outcomes of other products. Pricing rules and minimum requirements of various complementary and substitutional products may require careful design to avoid inefficiencies, duplication of revenues, bias toward or against specific generation technologies, and unintended consequences, for example on renewable energy curtailment. The interaction of capacity markets and ORDC scarcity pricing is particularly relevant for wholesale markets. Our results suggest multiple market structures can yield similar overall revenues and procurement of the desired amount of clean energy; we do not advocate for any particular capacity remuneration mechanism(s), though we note a potential substitutionary interaction between ORDC scarcity pricing and capacity markets. Indeed, actual markets have a range of capacity remuneration designs, from ORDC with no capacity market (e.g., ERCOT) to capacity market without ORDC (e.g., ISONE) to both ORDC and capacity market (e.g., PJM and NYISO), with ongoing activity in nearly every ISO/RTO to adjust and improve their region's individual design (Harvey, 2020; Sun et al., 2021). More research is needed to understand the nuanced, broader system-wide impacts of these designs and potential modifications (such as changes to the price caps) for optimal performance—and minimal complexity—in each specific market area.

3.3 Key Finding 3: Carbon pricing and CETs can both achieve clean energy goals.

Carbon pricing has been adopted or is being considered in jurisdictions around the world to incentivize clean energy technologies (World Bank, 2020). Here, we explore the impacts of carbon pricing on deployment, generation, and market clearing outcomes, focusing on interactions with CECs that are linked to CET policy targets.

Figure 17, which depicts the impact of carbon pricing on new deployment, reveals two key insights. First, at a low CET level, carbon pricing achieves greater deployment of carbon-free resources than a Mid CET policy alone without carbon pricing (compare ORDC_Carbon Low CET to ORDC Mid CET). We also see an overall reduction in gas-fired generators when carbon pricing is added, with a shift to more gas CCs and less gas CTs because of the lower carbon emission intensity of gas CCs. This highlights the efficacy of carbon pricing in incentivizing higher levels of clean energy resources and batteries, paticularly absent an aggressive CET. These trends are based on the assumed carbon pricing inputs; future work could explore the role of different carbon pice assumptions, either as exogenous inputs (as used here) or endogenously determined. See the SI for information on our inputs and future work.

The second key insight is that stacking multiple clean energy policies, which here consist of carbon pricing and CET policy that is linked to a CEC product, provides minimal decarbonization impacts at High CET levels; thus, only one well-designed policy is likely needed to achieve clean energy deployment for such a high target. This can be seen by the smaller incremental benefit of carbon pricing at the High CET level (compare ORDC to ORDC_Carbon).

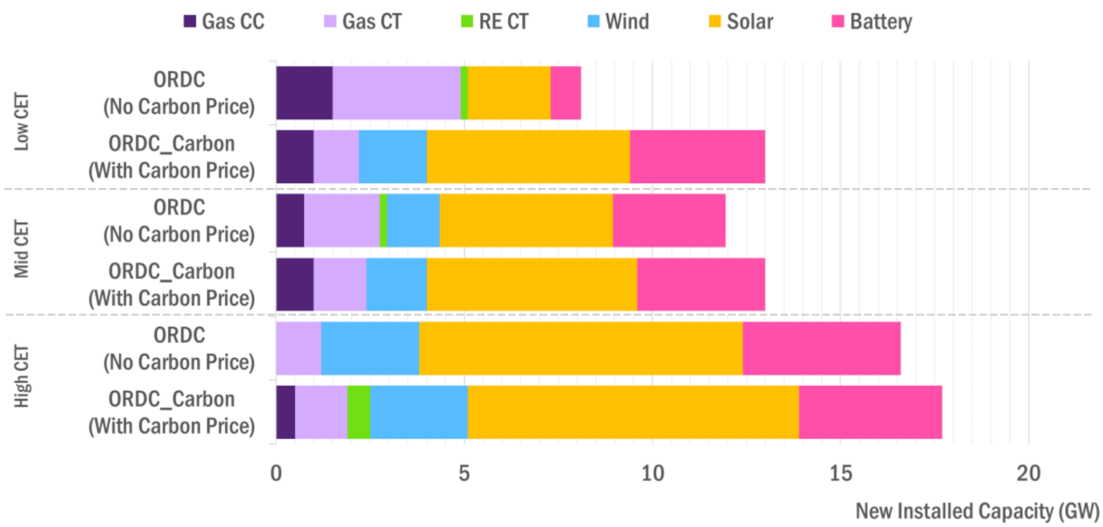

Figure 17. Total new capacity added during the simulation for the ORDC (without carbon pricing) versus the ORDC_Carbon (with carbon pricing) for each CET level.

These investment trends are also observed in the total generation outcomes (Figure 18), which show significantly greater clean energy utilization when carbon pricing is introduced at lower CET levels and much less difference at the High CET level. Interestingly, at the Low CET level, carbon pricing also leads to significantly larger renewable energy curtailment because of greater deployment of clean energy technologies. However, curtailment is not larger at High CET levels, where carbon pricing does not incentivize noticeably larger renewable capacities.

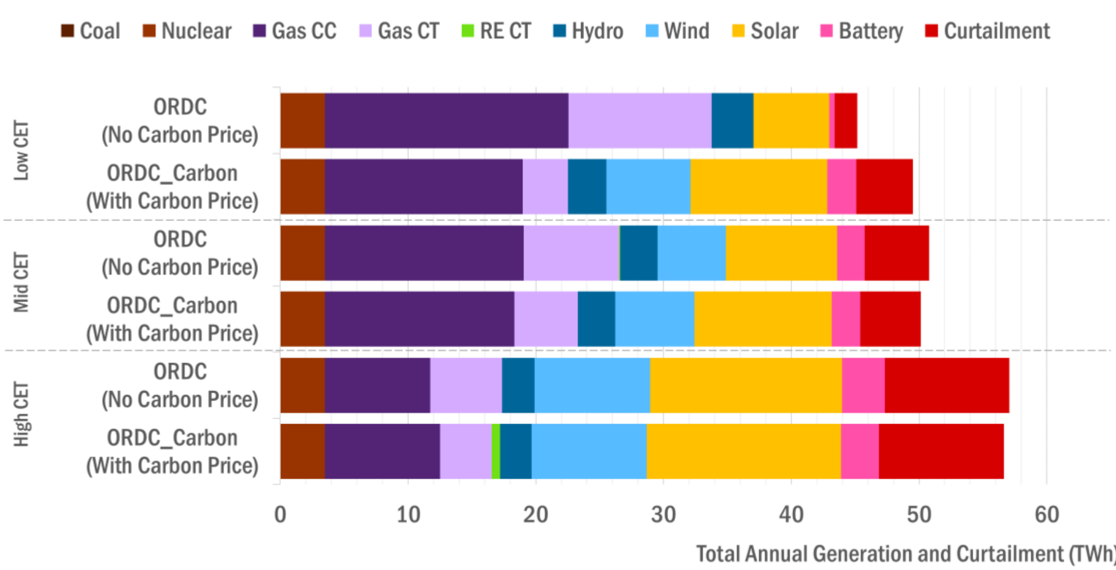

Figure 18. Total 2035 system-wide annual generation and curtailment for the ORDC (without carbon tax) versus the ORDC_Carbon (with carbon tax) for each CET level.

Figure 19 shows the impacts of carbon pricing on market revenue distribution. Expectedly, carbon pricing significantly increases energy market prices and revenues, particularly at lower CET levels, where cleaner generation technologies can benefit from the increased frequency of periods with higher marginal prices set by thermal generators with carbon pricing. Operating reserve revenues from ORDC products (i.e., Primary and Synchronous) also increase from a higher frequency of scarcity-induced pricing events. This is driven by the reduction of gas CT capacity and an overall reduction of online capacity to avoid incurring carbon prices. Collectively, these trends reduce the capacity available for reserve provision, resulting in times of insufficient capacity that trigger higher prices from the ORDC curves.

We also observe notable revenue interactions between carbon pricing and the CECs corresponding to each CET level. While the CEC revenues grow with increasing CET, introducing carbon pricing noticeably supresses CEC revenues. This is because significant increases in energy and operating reserve revenues due to carbon pricing lowers the generators' going-forward costs, thereby reducing the CEC market bids and clearing prices (see SI for bid formation details). These CEC revenue reductions are far outweighed by the larger energy and operating reserve revenues, resulting in larger overall revenues with carbon pricing, mostly at the Low and Mid CET levels. Though carbon pricing and CEC markets yield stark revenue distribution tradeoffs, they ultimately both push the system buildout in same direction. Therefore, as previously mentioned, carbon pricing and CEC markets as modeled here can exhibit a substitutional relationship whereby similar clean energy outcomes, especially for high CET levels, can be achieved by either mechanism.

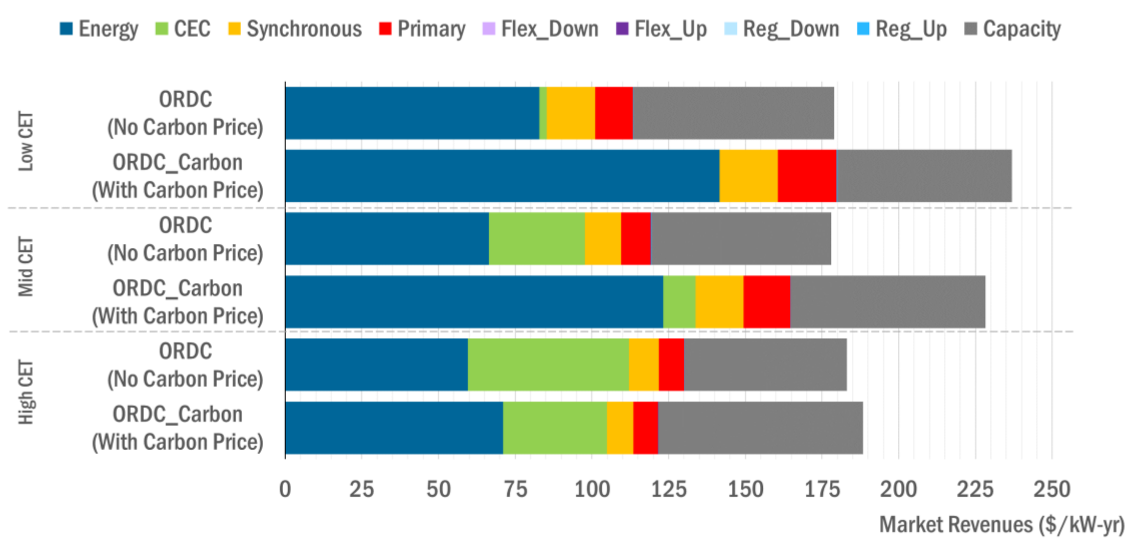

Figure 19. Annual market Revenues (averaged across the 15-year simulation horizon) for the ORDC (without carbon tax) versus the ORDC_Carbon (with carbon tax) across each CET level.

Finally, the impacts of carbon pricing on the profitability of investor firms are shown in Figure 20. Firms that only own thermal generation assets (i.e., IPP) experience significant reduction in profitability because of higher operating costs from carbon pricing. In contrast, firms with VRE resources (i.e., all except the IPP) have noticeably higher profits at the Low and Mid CET levels because of the significant increase in energy and reserve revenues, but they sometimes see reduced profits at the High CET level because the small increase in energy revenues due to carbon pricing at High CET levels is more than offset by the reduction in CEC revenues.

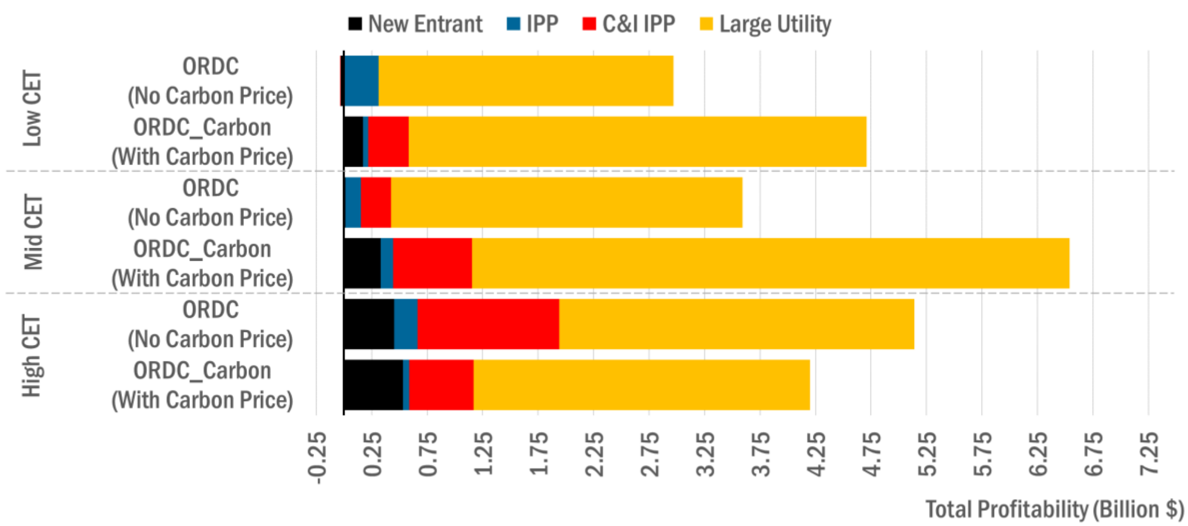

Figure 20. Total investor agent-level profitability (across the 15-year simulation horizon) for the ORDC (without carbon tax) versus the ORDC_Carbon (with carbon tax) across each CET level.

Market considerations: Our results demonstrate that absent an aggressive CET, carbon pricing can effectively drive greater deployment of clean energy technologies. We observe a potentially substitutional relationship between CEC markets and carbon pricing at high CET levels, indicating possible market redundancies—and extra complexity—by stacking both policies. Additionally, the smaller market revenues in the absence of a carbon price could also result in lower costs being passed on to ratepayers in regulated markets and potentially also in competitive market areas; however, we caution against a direct conclusion from this work, as retail rates were not included, and revenues do not necessarily capture ratepayer cost trends. Work is needed to further explore this potential impact and how both markets and clean energy policies could be best designed to benefit ratepayers. Though this analysis explored one set of stylized clean energy policies, additional designs can also be evaluated to account for the myriad design considerations and impacts, including cross-border treatment, the level of market competition, the impact of stacking policies (including cost subsidies), the cost pass-down to end users, the price interaction with energy markets (such as that proposed by the New York Independent System Operator (NYISO, 2018)), and the overall efficiency and efficacy, which depend greatly on the design (Bushnell et al., 2014; Caron et al., 2018; Xu and Hobbs, 2021).

3.4 Key Finding 4: Market rules that restrict participation of clean energy resources in capacity markets can result in reduced aggregate installed capacity and generation of those clean technologies, but with nuanced differences among individual clean energy technologies.

Our fourth key finding focuses on participation rules for capacity markets, including the ability for wind, solar, and/or battery technologies to clear in the forward capacity market (No_VRE_Cap_Mkt and No_VRE_Bat_Cap_Mkt scenarios) and the capacity credit (or derating factor) that determines the percentage of wind, solar, and battery nameplate capacity that is eligible to participate in the forward capacity market (Half_CCredit and Double_CCredit scenarios). These sensitivity cases serve as stylized representations of ongoing discussions on capacity market rules, including minimum bid price rules (such as the MOPR, which can effectively prevent resources from clearing the market) and capacity credit calculation methods. Because each of these scenarios includes a carbon price, we use the ORDC_Carbon scenario as our baseline comparison case. We focus on the Mid CET level because the relative impact of carbon pricing (ORDC versus ORDC_Carbon) is less significant than at the Low CET level, thereby minimizing any carbon price bias in the discussion here.

We find that limiting participation of wind, solar and/or batteries by reducing their capacity credit (Half_CCredit) or precluding them from capacity market participation (No_VRE_Cap_Mkt and No_VRE_Bat_Cap_Mkt) reduces their aggregate annual generation and installed capacity, and instead, increases that from gas CT and RE-CT generators (Figure 21 and Figure 22). Overall system-wide installed capacity is higher in these cases to meet both the capacity targets (as reflected in the capacity market demand curve) and clean energy goals, resulting in higher overall system cost (see the Mid CET results in the SI). Conversely, opposite trends are observed in the scenario where VRE and storage receive a larger capacity credit (Double_CCredit).

We also observe distinct tradeoffs between wind and the combination of solar and batteries. As shown in Figure 22, when batteries are not restricted (No_VRE_Cap_Mkt), they serve as a strong enabler of solar deployment but not wind, as also discussed in Section 3.1. However, when batteries are also restricted (No_VRE_Bat_Cap_Mkt), both battery and solar deployment is suppressed, accompanied by an increase in wind deployment, and consequently, higher renewable energy curtailment. These interactions highlight the need for careful consideration of how eligibility rules for one technology can impact not only that technology, but other technologies as well.

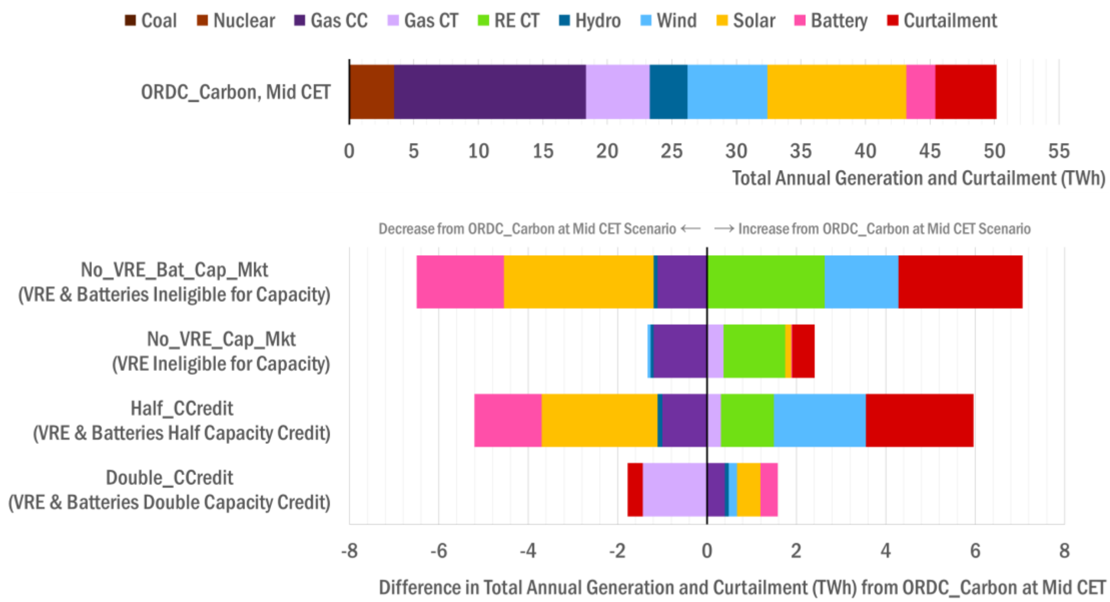

Figure 21. Difference in total annual generation and curtailment for the scenarios exploring capacity market participation (all include ORDC and a carbon tax) for the 75% CET level compared to the ORDC_Carbon scenario (shown in upper chart).

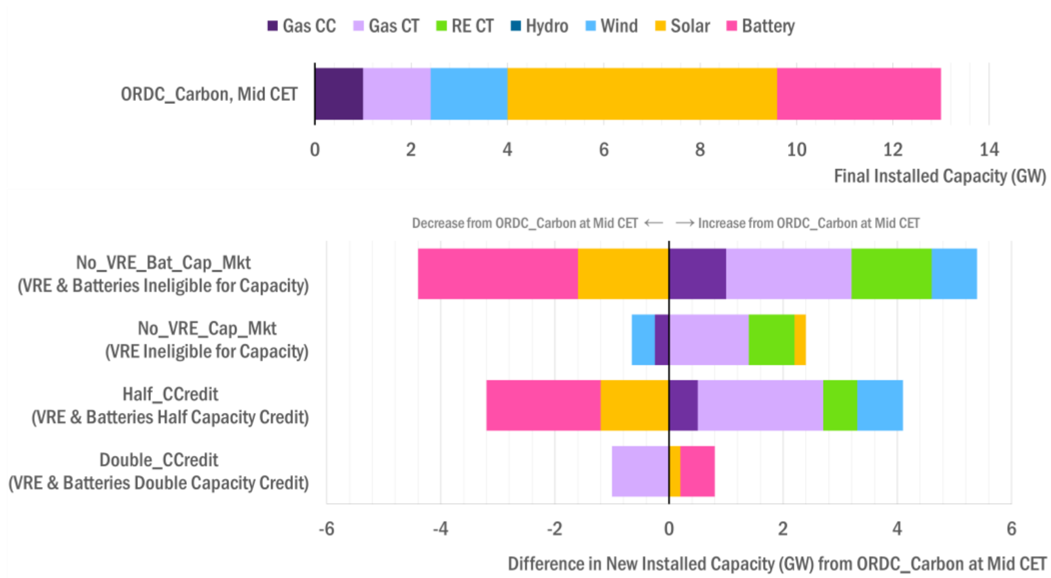

Figure 22. Difference in new capacity added during the simulation for the scenarios exploring capacity market participation (all include ORDC and a carbon tax) for the 75% CET level compared to the ORDC_Carbon scenario (shown in upper chart).

These generation shifts noticeably impact capacity market prices (Figure 23) and the distribution of revenues among products (Figure 24). With lower capacity credits and fewer eligible resources participating in the capacity market, capacity market prices are higher; the converse is true for the case with higher values of capacity credit (Double_CCredit).

In the scenario where wind, solar, and batteries cannot participate in the capacity market (No_VRE_Bat_Cap_Mkt), average capacity prices are slightly lower than the case where only wind and solar are excluded from capacity market participation (No_VRE_Cap_Mkt). This is because exclusion of batteries in the first case yields more operating reserve scarcity events, leading to higher energy and reserve market revenues (Figure 24), thereby suppressing capacity market bids and clearing prices (Figure 23).

Furthermore, Half-CC and No_VRE_Bat_Cap_Mkt scenarios also yield noticeably larger CEC market revenues (Figure 24), primarily because of higher CEC prices resulting from reduced solar deployment in these scenarios and the associated need for more clean energy capacity. These results demonstrate that adjusting market rules and eligibility criteria for one product can have spillover effects on the market clearing outcomes of other products, underscoring the need for careful market and policy design.

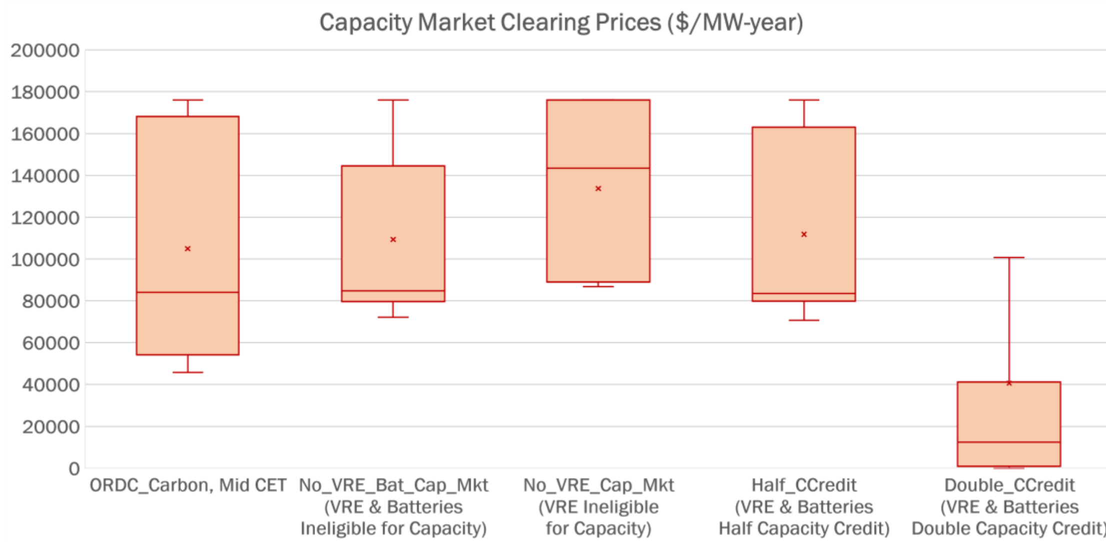

Figure 23. Distribution of annual capacity market clearing prices for scenarios exploring capacity market participation (all include ORDC and a carbon tax) for the 75% CET level. Asterisks show mean values; boxes include the 1st quartile, median, and 3rd quartile; whiskers are the minimum and maximum values (excluding outliers).

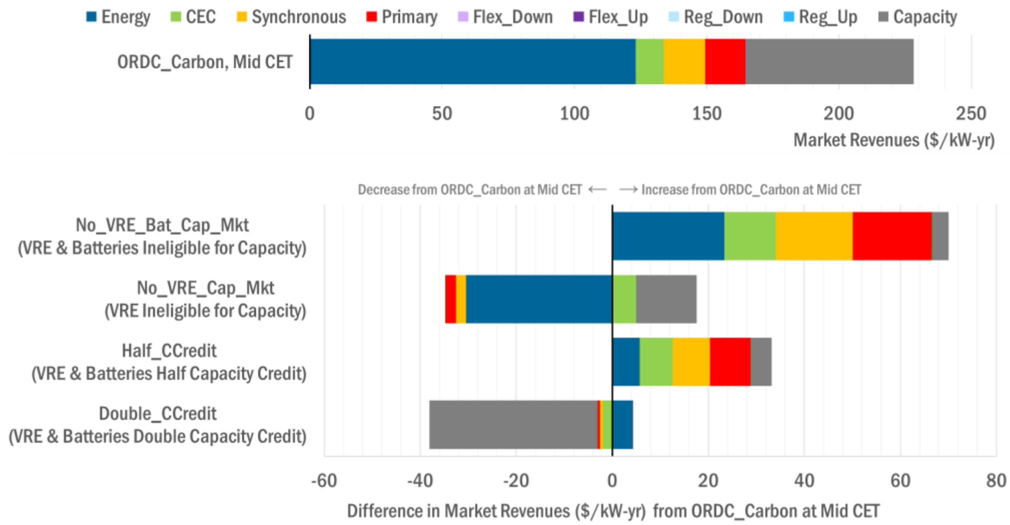

Figure 24. Difference in annual market revenues (averaged across the 15-year simulation horizon) for the scenarios exploring capacity market participation (all include ORDC and a carbon tax) for the 75% CET level compared to the ORDC_Carbon scenario (shown in upper chart).

As shown in Figure 25, these revenue distribution outcomes indicate that restricted participation of VRE and batteries in capacity markets can increase capacity-based revenues and overall profitability for investors owning eligible resources (IPP and Large Utility) but decrease profitability for firms only investing in VRE and batteries (New Entrant and C&I IPP). In the scenario where VRE and storage receive a larger capacity credit (Double_CCredit), we see the opposite trend.

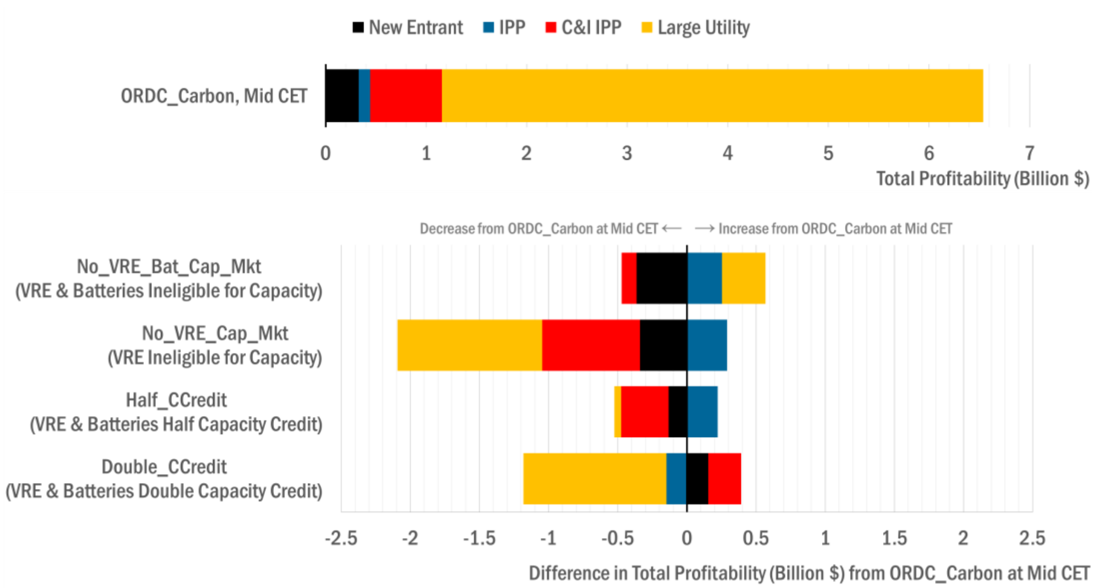

Figure 25. Difference in firm-level profitability (total across the 15-year simulation horizon) for the scenarios exploring capacity market participation (all include ORDC and a carbon tax) for the 75% CET level compared to the ORDC_Carbon scenario (shown in upper chart).

Market considerations: These results provide important market design implications related to eligibility rules for capacity markets, including the ability to participate in capacity markets and the capacity credit of wind, solar, and battery resources. Most notably, market rules that impact eligibility can hinder market efficiency and VRE utilization, as reflected by larger total system costs and higher levels of VRE curtailment. This suggests the need to move toward open markets with no eligibility restrictions – either explicit or implicit, such as through minimum bid offer rules like MOPR that effectively preclude clearing in the market – and with accurate accounting of the value of capacity, especially as systems and times of highest stress evolve. We also saw multiple instances of market outcome interdependencies. For example, adjusting market rules and eligibility criteria for one product can impact the market clearing outcomes of other products, and eligibility rules for one technology can have indirect but strong deployment impacts on not only that technology but other complementary technologies. This underscores the need for careful market and policy design that avoids unintended consequences for market efficiency, policy efficacy, and grid reliability.

3.5 Key Finding 5: Market rules that restrict participation of clean energy resources for providing operating reserves can result in significant price differences that further disfavor deployment of those clean energy technologies.

Our fifth key finding relates to the eligibility of wind, solar, and battery technologies to participate in operating reserve markets (No_VRE_Reserves and No_VRE_Bat_Reserves scenarios). Like the fourth key finding, we use the ORDC_Carbon scenario, but for the High CET level here, as our baseline case for comparison.

In general, restricting VRE and/or batteries from providing reserves results in a large increase in thermal generation (Figure 26) to meet the reserve requirements and a noticeable increase in both operation costs (see the SI) and curtailment (Figure 26). In cases where only wind and solar are restricted from providing reserves (No_VRE_Reserves), solar and battery generation increase, while wind generation decreases (Figure 26). However, when batteries are also restricted (No_VRE_Bat_Reserves), we see an increase in wind generation while solar and battery generation decrease (Figure 26). These operational results again highlight the strong synergistic relationship between solar and battery resources, as also identified in Sections 3.1 and 3.4. We see similar but more pronounced impacts on new capacity additions (see SI). These trends also align with previous PCM work, which found that excluding wind and solar from providing reserves requires committing additional thermal generators to meet those operating reserve requirements (Frew et al., 2021a) and that battery storage can capture most of the benefit of providing operating reserves from among other IBRs like wind and solar (Frew et al., 2021b).

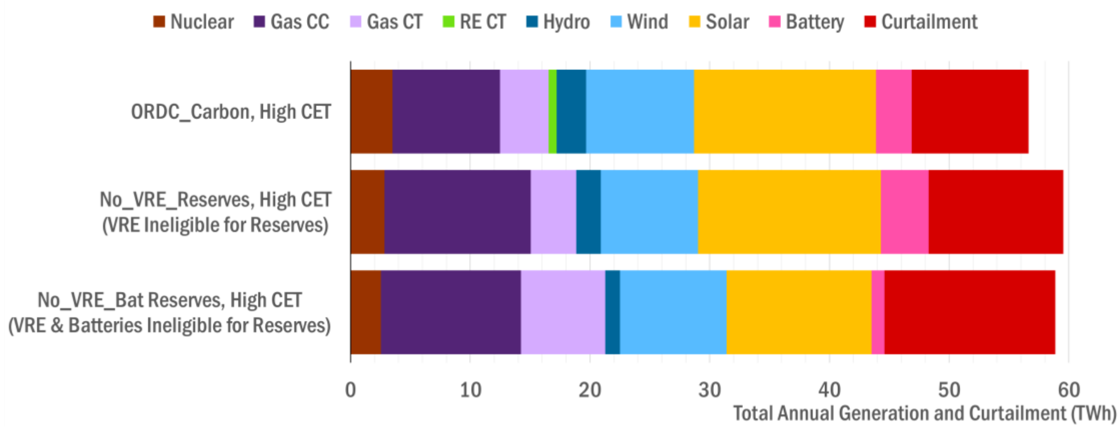

Figure 26. Total 2035 system-wide annual generation and curtailment for the scenarios exploring wind and solar participation in operating reserve markets (all include ORDC and a carbon tax) for the 100% CET level.

There are also important pricing and revenue impacts from these operating reserve eligibility restrictions. These are most prominent when wind, solar, and batteries are all precluded from providing operating reserves (No_VRE_Bat_Reserves), which sees a significantly higher frequency of ORDC Synchronous and Primary operating reserve scarcity pricing events that are driven by an insufficient pool of eligible resources. This results in larger Synchronous and Primary operating reserve prices and, in turn, energy prices (see Figure S4 in the SI). As shown in Figure 27, these high operating reserve prices yield significantly larger market revenues for operating reserves and energy, which in turn suppress capacity market revenues.

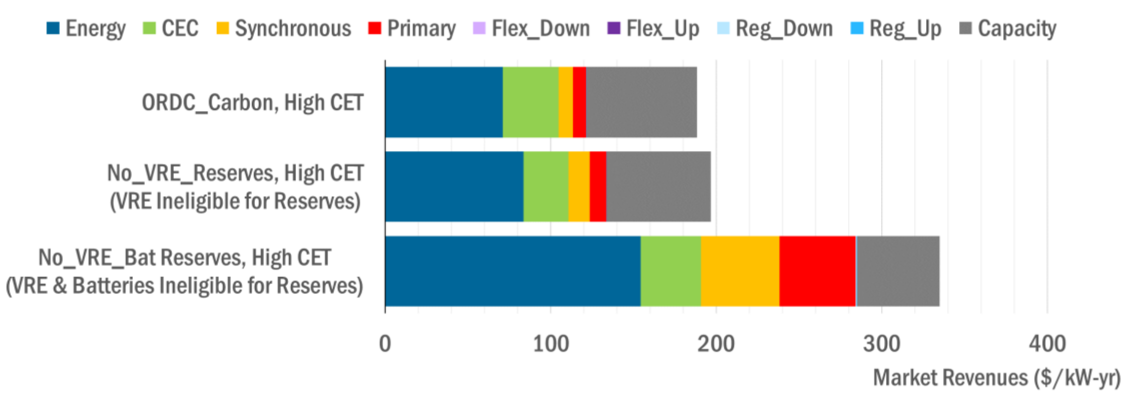

Figure 27. Annual market revenues (averaged across the 15-year simulation horizon) for the scenarios exploring wind, solar, and battery participation in operating reserve markets (all include ORDC and a carbon tax) for the 100% CET level.

These generation and scarcity-driven price shifts have distinct impacts on investor profitability (Figure 28), with New Entrant and C&I IPP profitability reduced when wind, solar, and/or batteries are not permitted to provide operating reserves. Conversely, the IPP and Large Utility profitability increases because of significantly larger energy and reserve revenues for their thermal generators, which receive high reserve prices in the absence of VRE and battery providing operating reserves. This is particularly true when wind, solar, and batteries are all excluded from providing operating reserves and scarcity pricing is more prevalent.

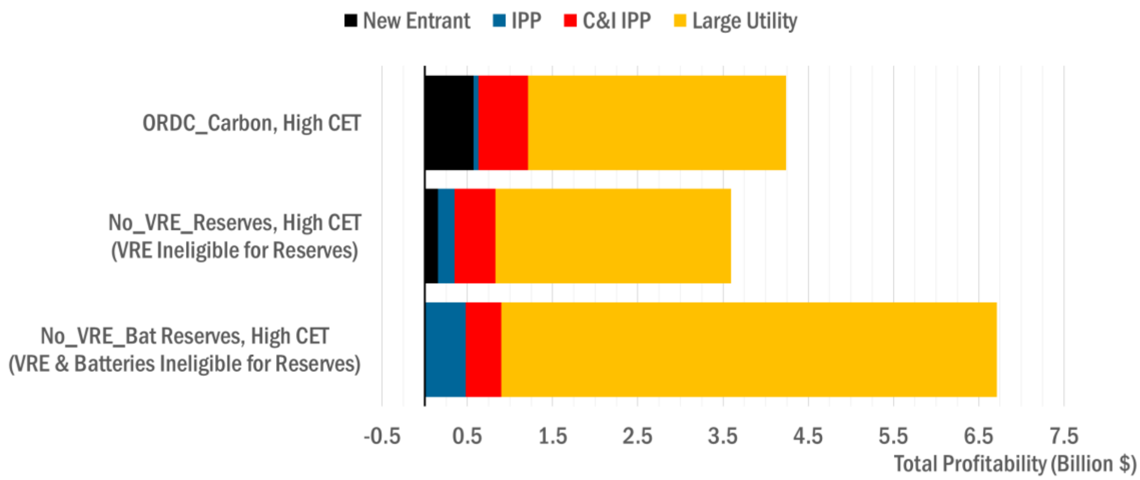

Figure 28. Firm-level profitability (total across the 15-year simulation horizon) for the scenarios exploring wind, solar, and battery participation in operating reserve markets (all include ORDC and a carbon tax) for the 100% CET level.

Market consideration: These results provide important market design implications related to eligibility rules for operating reserve markets. Most notably, market rules that preclude participation by certain technologies can hinder market efficiency and VRE utilization, as reflected by higher frequency of scarcity-induced pricing events, higher total cost, and higher levels of curtailment. Additionally, rules for one technology can have indirect but strong deployment impacts on complementary technologies; this was particularly true for batteries, whose eligibility status more strongly impacted the generation and deployment of solar than of that for solar itself. This highlights the important role of storage in market structures with high CETs and presents a caution for unintended consequences in designing operating rules for futures systems.

3.6 Key Finding 6: At high CETs, adding an inertia product can favor technologies that support both the technical capability and overarching policy goal but also result in potentially redundant resource utilization.

Maintaining stable frequency is a significant concern with increasing integration of IBRs. Our sixth key finding results from the addition of an inertia product as a possible mitigation strategy. This product allows substitutional provision of fast frequency response (FFR) by wind, solar, and battery IBR technologies based on available headroom, assuming proper software and/or control capability (see the SI for model details). We again use the ORDC_Carbon scenario as our baseline case, with a focus on the Low and High CET levels.

Figure 29 shows that adding an inertia product noticeably increases the installed capacities of gas CTs, particularly at high CETs. Additionally, wind is replaced with higher capacities of RE-CTs, which can provide more inertia while also meeting the CET. Similar trends were observed for generation (see SI), especially increased RE-CT and gas CT generation that is enabled by commitment of these generators to help meet the inertia requirement and, in the case of the RE-CTs, also the CET target. The increased utilization of these high-cost CT generators to meet the inertia constraint, while still operating wind, solar, and battery technologies to meet the CET, results in larger operating costs and curtailment (see the SI), indicating less efficient and potentially redundant operations.

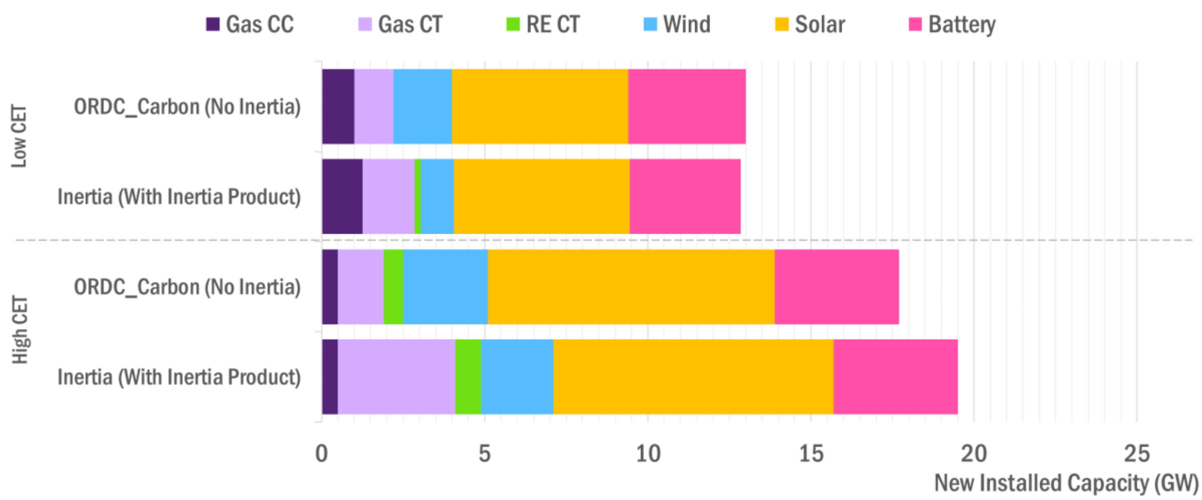

Figure 29. Total new capacity added during the simulation for the ORDC_Carbon (without an Inertia product) and the Inertia scenarios for the 45% and 100% CET levels.

Figure 30 summarizes the impacts of including an inertia product on the distribution of market revenues. We see two distinct trends. At the Low CET level, adding an inertia product reduces total operating reserve revenues because the minimum inertia requirement forces greater thermal generation capacity to be online, providing greater overall operating reserve provision availability and consequently lower reserve prices. The reduction in reserve prices also suppresses energy prices and revenues. Conversely, for the High CET level, significantly larger deployment of IBRs results in more periods with inertia scarcities (20% of the timesteps in the final solve year, compared to 5% for the Low CET and 6% for the Mid CET), resulting in higher inertia prices and revenues, and in turn, higher energy prices and revenues.

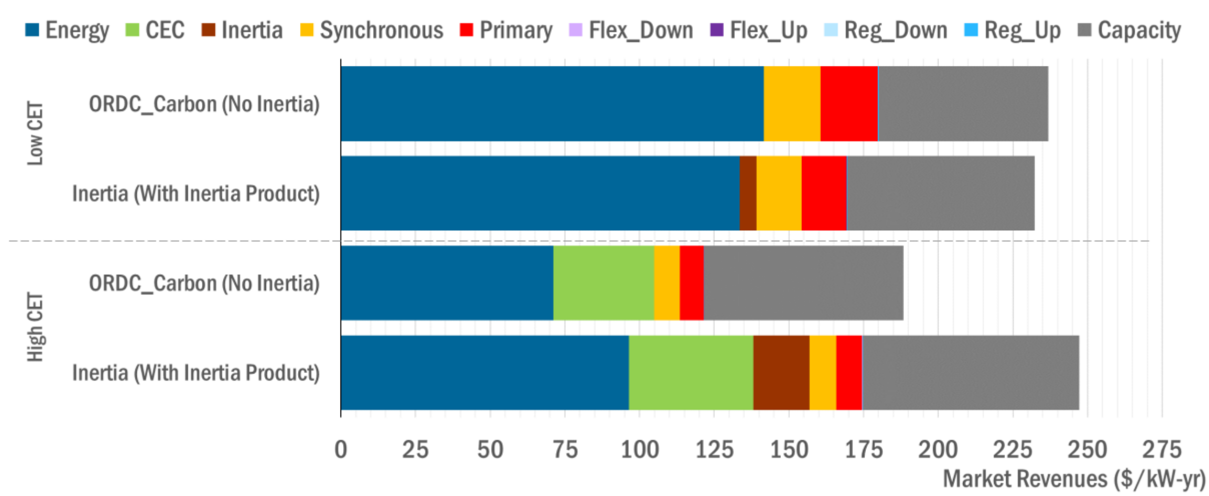

Figure 30. Annual market revenues (averaged across the 15-year simulation horizon) for the ORDC_Carbon (without an Inertia product) and Inertia scenarios for the 45% and 100% (Low and High respectively) CET levels.

Market considerations: Our results suggest that adding an inertia product to support stable frequency might only noticeably affect prices and system operations at very high CETs. We see larger deployment and utilization of gas CTs and RE-CTs to help meet these inertia requirements. Even with additional CT generators and the contribution of FFR from IBRs toward the inertia requirement, the system still experiences significant inertia scarcities at high CET levels. Therefore, absent FFR capabilities, even higher scarcity pricing or investments in alternative clean energy resources with traditional inertial response (such as RE-CTs) can be expected, both of which would result in larger total system costs. Additionally, inertia markets would need to be carefully designed, striking a balance among satisfying the system's physical requirements, meeting CETs, and avoiding potential economic inefficiencies—and complexity—that are due to resource redundancies.

4. Conclusions and Policy Implications

This paper uses the EMIS-AS model to evaluate the effectiveness of a wide range of wholesale electricity market structures in achieving decarbonization policy goals, while considering the impact on market clearing outcomes and the risk and adaptive behavioral elements of firm-level investment decision-making.

Overall, our analysis across 51 scenarios on a test system points to the need for an appropriate balance of market design complexity with consideration of unintended consequences, given the interconnected nature of markets with system-wide operations and investment. This multi-dimensional market design challenge is a complexity conundrum, whereby adding multiple market products and/or rules can sometimes significantly increase complexity without providing additional benefit to the grid physics, economics, or policy goals. We observe six specific key findings on the effectiveness of different market structures in achieving decarbonization policy goals, the nuanced and often non-incremental interactions among various market products and design constructs, and the consequent impacts on firms' profitability.

First, results show that carefully designed energy-only markets can achieve similar clean energy targets (CETs) as those with forward capacity market structures, but with different underlying revenues distributions. We find that the presence of capacity markets favors investors with low investment cost peaking thermal units (gas CTs) and therefore, it is important to design these market structures to avoid biasing generation technologies and investor types. Future work could explore the impact of these structures on retail rates and reliability under a wider set of system conditions using extreme weather data sets and/or linkages with probabilistic resource adequacy models.

Second, operating reserve demand curve (ORDC) scarcity pricing mechanisms facilitate greater investments in flexible generation resources (i.e., CTs and batteries) but yield noticeably greater levels of VRE curtailment because those CTs must be kept online more often to avoid triggering scarcity pricing events, thereby reducing VRE utilization. We also find that ORDC pricing can have a substitutional relationship with a capacity market in overall generator deployment, indicating possible market inefficiencies if the market rules are not carefully formulated.

Third, if properly designed, carbon pricing can be an effecive mechanism for achieving clean energy goals, especially if a CET is low or not defined. Furthermore, stacking multiple carbon policies (carbon pricing and CET linked to a CEC product in this analysis) provides minimal decarbonization benefits at high CET levels, indicating that only one well-designed policy is likely needed to achieve aggressive clean energy deployment goals.

Fourth, rules that restrict participation of certain technologies in capacity markets – such as mechanisms that preclude clearing in the market or reduce the eligible portion of capacity that can participate – can result in significant deployment and operational differences, even for technologies that are not restricted. Market rules and eligibility criteria for one product may have unintended and nonintuitive spillover effects on the market clearing outcomes of other products, underscoring the need for careful market and policy design that minimize these unintended consequences.

Fifth, market rules that limit the eligibility of certain technologies from providing operating reserves can hinder market efficiency and VRE utilization, as reflected by higher frequency of scarcity-induced pricing events, higher total cost, and higher levels of curtailment. We again see strong tradeoffs between certain technologies, especially between wind-and-gas versus solar-and-battery technologies in both generation and deployment, highlighting the strong role that market eligibility rules can have on not only operations but also investment decisions. The particularly strong role of battery eligibility in impacting price and operation outcomes underscores the need to better understand the interaction of this more complex technology with still-evolving market rules.

Sixth, adding an inertia product may only noticeably affect prices and system operations at very high CETs, where significant scarcity events occur even with additional gas CT and RE-CT resources and with the contribution of wind, solar, and battery headroom-based FFR. While more work is needed to understand the exact inertial needs and capabilities of the system – which ultimately point to the requirement for maintaining system frequency – any inertia markets should be carefully designed to satisfy the system's physical requirements, meet CETs, and avoid potential economic inefficiencies from resource redundancies.

Overall, our results reveal that interactions between various market structures are heavily nuanced and must be designed carefully to maximize market efficiency, avoid unintended consequences, and drive desired policy goals. We focus on highly decarbonized futures with hourly day-ahead and 5-min real-time market simulations for one weather year. Future work is needed to understand the interactions of market designs across additional system conditions like extreme weather events, as well as with consideration of additional grid physics at finer timescales, such as voltage and frequency. Future work could also explore the tension between markets versus mandates as mechanisms for supporting the full set of essential grid services. We also note that our analysis provides high-level insights into the above qualitative trends using a stylized test system. Thus, our results are not specific to any actual system, and work is needed to establish trends across a more diverse set of system configurations. Additional future work possibilities are discussed in the SI; we highlight the particular importance of price responsive demand that can reflect its true value of reliability (Redefining Resource Adequacy Task Force, 2021).

Acknowledgements

This work was authored by the National Renewable Energy Laboratory (NREL), operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. A portion of this research was performed using computational resources sponsored by the Department of Energy's Office of Energy Efficiency and Renewable Energy and located at NREL. Funding was provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Strategic Analysis Team. The authors especially thank Paul Spitsen (DOE) for sponsoring this work and Jonghwan Kwon (Argonne National Laboratory), Rob Gramlich (Grid Strategies LLC), Mark O'Malley (Energy Systems Integration Group and University College Dublin), Juha Kiviluoma (VTT Technical Research Centre of Finland), Mark Ahlstrom (NextEra Energy Resources), Paul Denholm, Gian Porro, Daniel Steinberg, Jaquelin Cochran, and Dave Corbus (all NREL) for providing valuable feedback on the draft of this paper. We note that the results and any error in this work are the sole responsibility of the authors, and no responsibility is given to any external parties. We are also grateful for the editorial support provided by Mike Meshek (NREL). The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

References

Anwar, M.B., Dalvi, S., Stephen, G., Frew, B., Ericson, S., Valqui Ordonez, B., Brown, M., Biagioni, D., Program, U.L.D.R. and D. (LDRD), 2020. EMIS Agent Simulation Model (Electricity Markets Investment Suite) (No. EMIS-AS (EMIS Agent Simulation Model)). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.11578/dc.20201026.3

Anwar, M.B., Stephen, G., Dalvi, S., Frew, B., Ericson, S., Brown, M., O'Malley, M., 2022. Modeling investment decisions from heterogeneous firms under imperfect information and risk in wholesale electricity markets. Applied Energy 306, 117908. https://doi.org/10.1016/j.apenergy.2021.117908

Asmine, M., Langlois, C.-É., Aubut, N., 2018. Inertial response from wind power plants during a frequency disturbance on the Hydro-Quebec system – event analysis and validation. IET Renewable Power Generation 12, 515–522. https://doi.org/10.1049/iet-rpg.2017.0392

Barazza, E., Strachan, N., 2020. The co-evolution of climate policy and investments in electricity markets: Simulating agent dynamics in UK, German and Italian electricity sectors. Energy Research & Social Science 65, 101458. https://doi.org/10.1016/j.erss.2020.101458

Barrows, C., Bloom, A., Ehlen, A., Ikaheimo, J., Jorgenson, J., Krishnamurthy, D., Lau, J., McBennett, B., O'Connell, M., Preston, E., Staid, A., Stephen, G., Watson, J.-P., 2019. The IEEE Reliability Test System: A Proposed 2019 Update. IEEE Transactions on Power Systems 35. https://doi.org/10.1109/TPWRS.2019.2925557

Botterud, A., Mahalik, M.R., Veselka, T.D., Ryu, H.-S., Sohn, K.-W., 2007. Multi-Agent Simulation of Generation Expansion in Electricity Markets, in: 2007 IEEE Power Engineering Society General Meeting. Presented at the 2007 IEEE Power Engineering Society General Meeting, pp. 1–8. https://doi.org/10.1109/PES.2007.385566

Bushnell, J., Chen, Y., Zaragoza-Watkins, M., 2014. Downstream regulation of CO2 emissions in California's electricity sector. Energy Policy 64, 313–323. https://doi.org/10.1016/j.enpol.2013.08.065

C2ES (Center for Climate and Energy Solutions), 2019. Clean Energy Standards: State and Federal Policy Options and Considerations. Arlington, VA.

California Air Resources Board (CARB), 2021. Cap-and-Trade Program: Frequently Asked Questions.

Caron, J., Cohen, S.M., Brown, M., Reilly, J.M., 2018. Exploring the impacts of a national u.s. co2 tax and revenue recycling options with a coupled electricity-economy model. Clim. Change Econ. 09, 1840015. https://doi.org/10.1142/S2010007818400158

Chappin, E.J.L., de Vries, L.J., Richstein, J.C., Bhagwat, P., Iychettira, K., Khan, S., 2017. Simulating climate and energy policy with agent-based modelling: The Energy Modelling Laboratory (EMLab). Environmental Modelling & Software 96, 421–431. https://doi.org/10.1016/j.envsoft.2017.07.009

Chen, H., Wang, C., Cai, W., Wang, J., 2018. Simulating the impact of investment preference on low-carbon transition in power sector. Applied Energy 217, 440–455. https://doi.org/10.1016/j.apenergy.2018.02.152

Cole, W., Frew, B., Gagnon, P., Reimers, A., Zuboy, J., Margolis, R., 2018. Envisioning a low-cost solar future: Exploring the potential impact of Achieving the SunShot 2030 targets for photovoltaics. Energy (Oxford) 155. https://doi.org/10.1016/j.energy.2018.04.166

Cole, W.J., Greer, D., Denholm, P., Frazier, A.W., Machen, S., Mai, T., Vincent, N., Baldwin, S.F., 2021. Quantifying the challenge of reaching a 100% renewable energy power system for the United States. Joule 5, 1–17. https://doi.org/10.1016/j.joule.2021.05.011

de Sisternes, F.J., Jenkins, J.D., Botterud, A., 2016. The value of energy storage in decarbonizing the electricity sector. Applied Energy 175, 368–379. https://doi.org/10.1016/j.apenergy.2016.05.014

Denholm, P., Arent, D.J., Baldwin, S.F., Bilello, D.E., Brinkman, G.L., Cochran, J.M., Cole, W.J., Frew, B., Gevorgian, V., Heeter, J., Hodge, B.-M.S., Kroposki, B., Mai, T., O'Malley, M.J., Palmintier, B., Steinberg, D., Zhang, Y., 2021. The challenges of achieving a 100% renewable electricity system in the United States. Joule. https://doi.org/10.1016/j.joule.2021.03.028

Denholm, P.L., Sun, Y., Mai, T.T., 2019. An Introduction to Grid Services: Concepts, Technical Requirements, and Provision from Wind (No. NREL/TP-6A20-72578). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1493402

Ela, E., Mills, A., Gimon, E., Hogan, M., Bouchez, N., Giacomoni, A., Ng, H., Gonzalez, J., DeSocio, M., 2021. Electricity Market of the Future: Potential North American Designs Without Fuel Costs. IEEE Power and Energy Magazine 19, 41–52. https://doi.org/10.1109/MPE.2020.3033396

EPRI, 2019. Ancillary Services in the United States: Technical Requirements, Market Designs and Price Trends (No. 3002015670).

EPRI, 2016. Wholesale Electricity Market Design Initiatives in the United States: Survey and Research Needs (No. 3002009273). Electric Power Research Institute, Palo Alto, CA.

ERCOT, 2018. Inertia: Basic Concepts and Impacts on the ERCOT Grid.

Frazier, A.W., Cole, W., Denholm, P., Greer, D., Gagnon, P., 2020. Assessing the potential of battery storage as a peaking capacity resource in the United States. Applied Energy 275, 115385. https://doi.org/10.1016/j.apenergy.2020.115385

Frew, B., Brinkman, G., Denholm, P., Narwade, V., Stephen, G., Bloom, A., Lau, J., 2021a. Impact of operating reserve rules on electricity prices with high penetrations of renewable energy. Energy Policy 156, 112443. https://doi.org/10.1016/j.enpol.2021.112443

Frew, B., Cole, W., Denholm, P., Frazier, A.W., Vincent, N., Margolis, R., 2019. Sunny with a Chance of Curtailment: Operating the US Grid with Very High Levels of Solar Photovoltaics. iScience 21, 436–447. https://doi.org/10.1016/j.isci.2019.10.017

Frew, B., Gallo, G., Brinkman, G., Milligan, M., Clark, K., Bloom, A., 2016. Impact of Market Behavior, Fleet Composition, and Ancillary Services on Revenue Sufficiency (No. NREL/TP-5D00-66076). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1262198

Frew, B., Sergi, B., Denholm, P., Cole, W., Gates, N., Levie, D., Margolis, R., 2021b. The curtailment paradox in the transition to high solar power systems. Joule 5. https://doi.org/10.1016/j.joule.2021.03.021

Frew, B.A., Cole, W.J., Sun, Y., Mai, T.T., Richards, J., 2017. 8760-Based Method for Representing Variable Generation Capacity Value in Capacity Expansion Models: Preprint (No. NREL/CP-6A20-68869). National Renewable Energy Laboratory (NREL), Golden, CO (United States).

Haegel, N.M., Margolis, R., Buonassisi, T., Feldman, D., Froitzheim, A., Garabedian, R., Green, M., Glunz, S., Henning, H.-M., Holder, B., Kaizuka, I., Kroposki, B., Matsubara, K., Niki, S., Sakurai, K., Schindler, R.A., Tumas, W., Weber, E.R., Wilson, G., Woodhouse, M., Kurtz, S., 2017. Terawatt-scale photovoltaics: Trajectories and challenges. Science 356, 141–143. https://doi.org/10.1126/science.aal1288

Harvey, S., 2020. CAISO Market Surveillance Committee: Scarcity pricing background discussion.

Hummon, M., Denholm, P., Jorgenson, J., Palchak, D., Kirby, B., Ma, O., 2013. Fundamental Drivers of the Cost and Price of Operating Reserves (No. NREL/TP-6A20-58491). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1220216

Hytowitz, R.B., Frew, B., Stephen, G., Ela, E., Singhal, N., Bloom, A., Lau, J., 2020. Impacts of Price Formation Efforts Considering High Renewable Penetration Levels and System Resource Adequacy Targets (No. NREL/TP-6A20-74230). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1659808

Ibanez, E., Brinkman, G., Hummon, M., Lew, D., 2012. Solar Reserve Methodology for Renewable Energy Integration Studies Based on Sub-Hourly Variability Analysis: Preprint (No. NREL/CP-5500-56169). National Renewable Energy Lab. (NREL), Golden, CO (United States).

Jenkins, J.D., Luke, M., Thernstrom, S., 2018. Getting to Zero Carbon Emissions in the Electric Power Sector. Joule 2, 2498–2510. https://doi.org/10.1016/j.joule.2018.11.013

Kell, A., Forshaw, M., McGough, A.S., 2019. ElecSim: Monte-Carlo Open-Source Agent-Based Model to Inform Policy for Long-Term Electricity Planning, in: Proceedings of the Tenth ACM International Conference on Future Energy Systems, E-Energy ’19. Association for Computing Machinery, New York, NY, USA, pp. 556–565. https://doi.org/10.1145/3307772.3335321

Khazaei, J., Tu, Z., Liu, W., 2020. Small-Signal Modeling and Analysis of Virtual Inertia-Based PV Systems. IEEE Transactions on Energy Conversion 35, 1129–1138. https://doi.org/10.1109/TEC.2020.2973102

Kraan, O., Kramer, G.J., Nikolic, I., 2018. Investment in the future electricity system - An agent-based modelling approach. Energy 151, 569–580. https://doi.org/10.1016/j.energy.2018.03.092

Kwon, J., Zhou, Z., Levin, T., Botterud, A., 2020. Resource Adequacy in Electricity Markets with Renewable Energy. IEEE Transactions on Power Systems 35, 773–781. https://doi.org/10.1109/TPWRS.2019.2930934

Kwon, J., Zhou, Z., Levin, T., Botterud, A., 2018. A Stochastic Multi-Agent Resource Planning Model: The Impact of Capacity Remuneration Mechanisms, in: 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS). Presented at the 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), pp. 1–6. https://doi.org/10.1109/PMAPS.2018.8440279

Levin, T., Botterud, A., 2015. Electricity market design for generator revenue sufficiency with increased variable generation. Energy Policy 87, 392–406. https://doi.org/10.1016/j.enpol.2015.09.012

Levin, T., Kwon, J., Botterud, A., 2019. The long-term impacts of carbon and variable renewable energy policies on electricity markets. Energy Policy 131, 53–71. https://doi.org/10.1016/j.enpol.2019.02.070

Mays, J., Morton, D.P., O'Neill, R.P., 2019. Asymmetric risk and fuel neutrality in electricity capacity markets. Nat Energy 1–9. https://doi.org/10.1038/s41560-019-0476-1

NYISO, 2018. Integrating Public Policy Task Force Carbon Pricing Proposal.

Park, H.-S., Jun, C.-H., 2009. A simple and fast algorithm for K-medoids clustering. Expert Systems with Applications 36, 3336–3341. https://doi.org/10.1016/j.eswa.2008.01.039

Peter Cramton, Emmanuele Bobbio, David Malec, Pacharasut Sujarittanonta, 2021. Electricity Markets in Transition: A multi-decade micro-model of entry and exit in advanced wholesale markets.

PJM, 2020. PJM Day Ahead Reserve Requirements. PJM.

Redefining Resource Adequacy Task Force, 2021. Redefining Resource Adequacy for Modern Power Systems. Energy Systems Integration Group, Reston, VA.

Reeg, M., Nienhaus, K., Roloff, N., Hauser, W., Wassermann, S., Weimer-Jehle, W., Klann, U., Kast, T., 2017. AMIRIS – An Agent-Based Simulation Model for the Analysis of Market Integration of Renewable Energies under Various Energy Policy Frameworks. undefined.

Rocha-Garrido, P., 2018a. Simplified Operating Reserve Demand Curve (ORDC) Enhancements.

Rocha-Garrido, P., 2018b. ORDC Supplemental Information.

RTS-GMLC: Reliability Test System - Grid Modernization Lab Consortium [WWW Document], 2018. URL https://github.com/ GridMod/RTS-GMLC

Sun, Y., Frew, B., Levin, T., Hytowitz, R.B., Kwon, J., Mills, A.D., Xu, Q., Heidarifar, M., Singhal, N., de Mello, P., Ela, E., Botterud, A., Zhou, Z., Hobbs, B.F., Crespo Montanes, C., 2021. Research Priorities and Opportunities in United States Wholesale Electricity Markets (No. NREL/TP-6A20-77521). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1785331

Tao, Z., Moncada, J.A., Poncelet, K., Delarue, E., 2021. Review and analysis of investment decision making algorithms in long-term agent-based electric power system simulation models. Renewable and Sustainable Energy Reviews 136.

World Bank, 2020. State and Trends of Carbon Pricing 2020. World Bank, License: CC BY 3.0 IGO, Washington, DC.

Xu, Q., Hobbs, B.F., 2021. Economic efficiency of alternative border carbon adjustment schemes: A case study of California Carbon Pricing and the Western North American power market. Energy Policy 156, 112463. https://doi.org/10.1016/j.enpol.2021.112463

Zavadil, R., Zack, J., Miller, N., Piwko, R., Knowe, G.V., Jordan, G., 2009. Technical Requirements for Wind Generation Interconnection and Integration. ISONE.

Supplemental Information

The following sections provide details on the methods, inputs, and modeling framework used in this study, as well as additional results.

Detailed Methodology

This second provides details on the modeling methodology and parameters that were used in the study.

Agent-based modeling approach

EMIS-AS is an agent-based simulation tool that explores the impact of various market design structures on investment and retirement decisions of heterogeneous, profit-seeking investor firms with imperfect information and bounded rationality. Market design structures could include the presence/absence of certain products, eligibility and pricing rules associated with those products, and the operational representation (e.g., sequence, resolution, lookahead). As shown in Figure S1, EMIS-AS consists of a series of simulation/optimization steps with a mixture of investor firm-level components and system-wide components. We highlight six high-level steps at the core of the EMIS-AS functionality. We refer readers to (Anwar et al., 2022, 2020) for a detailed description of the model.

1. After first initializing the model (loading preprocessing input data on the physical system, generator technologies, and market design configuration), each investor firm independently estimates future prices, generator portfolios, and generator capacity factors using a generation expansion planning (GEP) model. This GEP uses a set of representative days (based on k-medoids clustering of wind, load, and solar data (Park and Jun, 2009)) and generator capacity credits (using an hourly-based method for wind, solar, and batteries). If uncertainty is included, the GEP is solved for each separate future expectation scenario, with a probability weight assigned to each of those futures such that the sum of probabilities across all scenarios is one.
2. Each investor firm uses the outputs from Step 1 to calculate the net present value (NPV) for each potential, planned, and existing generator for each future scenario. EMIS-AS explicitly tracks projects through various life cycle phases, so that once a firm decides to invest in a project, it enters the planned phase by going into the interconnection queue. Once the project has spent the required time in the queue, and if the economics remain favorable, the project goes under construction. Projects must pay a fee to enter the interconnection queue, but once construction begins, the fixed capital costs are assumed sunk.
3. Each investor firm makes final build/retire decisions based on the expected utility calculated using the NPV values from Step 2, the scenario probabilities from Step 1, and the firm's assumed risk profile.
4. After calculating the market bids based on their price and generator utilization predictions, each investor firm submits price/quantity bids to the market for each desired product for each eligible generator based on the final build/retire decisions from Step 3.
5. The wholesale market clears for each product based on the set of bids received across the full set of investor firms, allowing the firms to see the impact of their own and other firm's decisions on prices. If uncertainty is included, this is also when the firms realize the accuracy level of their individual expectation or belief about the future (in this example, applied to load growth). Energy and ancillary services/operating reserve are co-optimized in a two-stage (i.e., day-ahead and real-time) least-cost unit commitment and economic dispatch market simulation using a PCM. Capacity markets are cleared on an annual 3-year forward horizon. Clean energy credits (CECs) are cleared on an annual horizon.

6. Each firm updates its realized revenues and expectations(s) about the future (in this case, as applied to load growth) using Kalman Filters. The model moves forward one investment step and repeats.

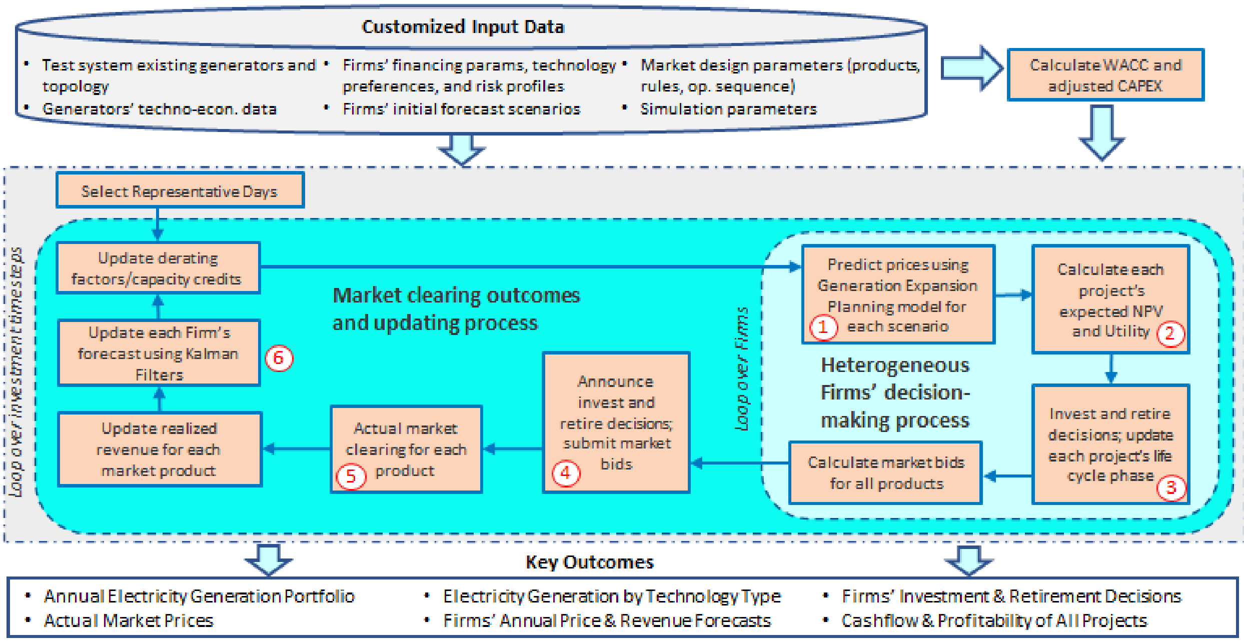

Figure S1. High-level summary of EMIS-AS framework with key steps highlighted

In this analysis, steps 1-3 are applied to investment steps of one year (each with a 10-year rolling horizon for price prediction), marching forward in time until the full 15-year solve horizon is complete. We nominally assume Year 1 is 2021, and the 15th year is 2035. Within each individual solve year, the GEP modeling in Step 1 is based on the same set of 20 representative days per year for each investment timestep. Those outputs are combined with exogenous discount rates and technology cost projections to calculate each project's cash flows across its remaining lifetime in Step 2 to determine whether to invest in or retire each project in Step 3. In this study, the energy-operating reserve co-optimization market clearing in Step 5 involves day ahead (DA) unit commitment at hourly resolution with a MIP gap of 0.05%, followed by real-time (RT) economic dispatch for each hour at a 5-min resolution using the binary unit commitment decisions fixed from the DA run. This DA-RT sequence is an improvement from the initial version of EMIS-AS as described in (Anwar et al., 2022). Step 5 includes clearing for a three-year forward capacity market, which is described in (Anwar et al., 2022) and includes a dynamic calculation of the capacity contribution of eligible wind, solar, and battery technologies. Step 5 also contains a CEC market, which is an extension of the renewable energy credit market in the initial version of EMIS-AS (Anwar et al., 2022).

Each project's market participation bids for the forward capacity and CEC markets are based on principles of revenue sufficiency, such that they reflect the project's "going-forward cost" which is defined as the difference between the project's annualized investment (and other fixed) costs and their expected net revenues from other markets). The capacity market is cleared maximizing total social welfare, which is modeled as the difference between the welfare associated with the cleared capacity demand (based on a downward-sloping elastic capacity demand curve) and the cost of the capacity supply (based on market bids of the participating projects). On the other hand, the CEC market assumes an inelastic demand curve, and therefore is cleared minimizing the total cost of CEC supply volume (based on CEC market bids) and the cost of violating the CEC target requirement (based on an exogenous alternative compliance payment). Details about the market clearing formulation of capacity and CEC markets equations can be referred to in (Anwar et al., 2022).

We note that the stepwise nature of this agent-based model inherently incorporates the imperfect information and uncertainty of actual investment and retirement decisions, and thus does not reflect a true equilibrium or co-optimized solution. Instead, EMIS-AS allows for recourse decisions by the firms as feedback effects are realized between the GEP projections from one year to the next, specifically when those conditions result in unfavorable project economics after an initial investment decision has been made. While the actual market clearing outcomes in Step 5 do not directly impact the subsequent year's investment decisions, they can impact retirement decisions which require a project to have a negative expected utility, negative expected profitability in the next year and realized losses in the previous two years. Key mechanisms that connect steps 1-3 with Step 5 include the forward capacity markets (by seeing what cleared in the previous year to inform additional decisions), retirement decisions as just described, and the update in expectations via Kalman Filters. Future work will further enhance this feedback via a performance multiplier in the utility function (Chen et al., 2018).

Realistic test system data set

For this analysis, we use the EMIS RTS-GMLC test system and a stylized set of four investor agents: New Entrant, independent power producer (IPP), commercial and industrial (C&I) IPP, and Large Utility that were previously explored and described in (Anwar et al., 2022). That test system has been modified from the IEEE Reliability Test System (RTS-GMLC) ("RTS-GMLC: Reliability Test System - Grid Modernization Lab Consortium," 2018) by removing all rooftop solar photovoltaic and concentrated solar power, as well as removing any nodal representation (i.e., all generation and demand within a given zone, or region, is collapsed on a single bus) and doubling the inter-zonal transmission capacity to accommodate higher generation demand and capacities in future years. The financial parameters for generation technologies are obtained from NREL's Annual Technology Baseline. To mitigate against unrealistic forecasting errors in the raw data set, we assume perfect foresight for wind and solar resources in the DA simulations (using an hourly average of the RT 5-min values) and an improved DA load forecast from the raw RTS data set (assuming a weighted blend of 2/3 DA forecast and 1/3 RT).

The four investor agents vary in size, expectations about the future, how confident they are in those expectations, their technology preferences, their perceived riskiness which impacts their financing parameters, and their risk profile, as summarized in Table S1. As in (Anwar et al., 2022), we apply uncertainty through the load growth, whereby each firm has a set of probability-associated estimates of future load growth and then updates those estimates in each investment step using Kalman Filters as they experience the simulated reality with its actual load growth and corresponding market clearing outcomes. The C&I IPP has the lowest load growth forecast (1.01%/year growth in their mid-case), the Large Utility has a mid-growth estimate (1.24%/year), and the New Entrant and IPP have the highest growth expectation (1.53%/year). The use of load growth uncertainty was for simplicity purposes, but future work with EMIS-AS could apply other sources of uncertainty within the existing model framework.

Table S1. Stylization of investor firms' heterogeneous attributes (adapted from (Anwar et al., 2022)[a])

Name	Mid Load Growth Forecast (Initial state estimate)	Confidence in Prediction (Initial error covariance)	Confidence in Measurement (Measurement covariance)	Investment Technology Preference	Capital Cost Multiplier	Perceived Riskiness	Risk Preference
New Entrant	1.53% p.a.	Low Confidence (1.0e0)	High Confidence (1.0e-4)	Wind, PV, Battery	High (1.143)	High (2.0%)	Very Risk Averse (1.0e-5)
IPP	1.53% p.a	Low Confidence (1.0e0)	High Confidence (1.0e-4)	Gas CC, Gas CT, RE-CT	Mid (1.105)	Mid (1.0%)	Very Risk Averse (1.0e-5)
C&I IPP	1.01% p.a.	Mid Confidence (1.0e-1)	Mid Confidence (1.0e-3)	Wind, PV	Mid (1.105)	Low (0.5%)	Risk Averse (1.0e-6)
Large Utility	1.24% p.a.	High Confidence (1.0e-3)	Mid Confidence (1.0e-2)	Gas CC, Gas CT, RE-CT, Wind, PV, Battery	Low (1.085)	None (0.0%)	Risk Averse (1.0e-6)

IPP: Independent Power Producer; C&I: Commercial and Industrial; PV: Photovoltaic; CC: Combined Cycle turbine; CT: Combustion Turbine; RE-CT: Renewable Energy CT; WACC: Weighted Average Cost of Capital; p.a: per annum

[a] Anwar, M.B., Stephen, G., Dalvi, S., Frew, B., Ericson, S., Brown, M., O'Malley, M., 2022. Modeling investment decisions from heterogeneous firms under imperfect information and risk in wholesale electricity markets. Applied Energy 306, 117908. https://doi.org/10.1016/j.apenergy.2021.117908

Market products and parameterizations

In addition to the EMIS-AS database and parameterization from (Anwar et al., 2022), we apply a series of enhancements to enable greater modeling capabilities and analysis dimensionality. Broadly speaking, these include additional market products and technology characterizations, which we further describe below for each individual enhancement.

The first model enhancement is increasing the set of operating reserve products to cover a wider range of response times. The version of EMIS-AS we used includes a set of ten possible market products: energy, forward capacity, CECs, inertia, and six operating reserve products. A summary of these six operating reserve product requirements and scarcity pricing assumptions (which reflect a typical operating reserve hierarchy, e.g., EPRI, 2019) are shown in Table S2. Within each product, eligible generators may provide operating reserves up to their operating limits (i.e., within ramping, maximum resource availability, and online status constraints). This study did not include operating reserve bids to reflect wear and tear costs (Hummon et al., 2013), operating reserves' nested response times to allow capacity to potentially supply multiple products with the same capacity if the response times overlap, response from offline generators (e.g., RE-CTs with synchronous condensers technically can provide inertial response while offline, see (Denholm et al., 2021), actual reserve deployment (i.e., release of held capacity to meet the operating reserve requirement), or mileage payments for services such as automatic generation control response for regulation. In all simulations, energy and operating reserves (which include inertia in scenarios with the inertia product) are fully co-optimized, which means in each time step, energy, operating reserves, and inertia are scheduled simultaneously from among all available resources to yield the lowest system-wide operating cost. Because these products are coordinated with consideration of each other, the clearing price for each will also account for any lost opportunity costs in addition to the actual operating cost (which is assumed to be zero for all operating products in this analysis). The lost opportunity cost reflects times when a unit is backed down from otherwise providing profitable energy to instead hold that capacity for operating reserves (EPRI, 2016).

In scenarios with operating reserve demand curve (ORDC) scarcity pricing mechanisms, the static scarcity pricing values shown in Table S2 are replaced with a probabilistic scarcity pricing curve for the Synchronous (i.e., spinning) and Primary (i.e., nonspinning) reserves. For each of these two operating reserve products, 24 ORDC scarcity pricing curves are implemented across different times of the day and year (4 seasons x 6 daily time blocks) to capture the changing risk levels in those time blocks. The ORDC curve formulations roughly follow the PJM methodology, which involves calculation of the net load forecast error distribution and generator unavailability distribution (based on forced outage rates) (Rocha-Garrido, 2018a, 2018b). These distributions are then combined to determine the probability of system reserves falling below the minimum reserve requirement (MRR) at different reserve levels. The MRR is defined as 100% and 150% of the nameplate capacity of the largest generator in the system for Synchronous and Primary reserves respectively (PJM, 2020), which translate to 400 MW and 600 MW for the test system used in this study. The probabilities are then multiplied by the maximum scarcity price to determine the ORDC penalty price at each reserve level. The curves are updated each solve year based on the previous year's installed capacity and timeseries profiles for load, wind and solar.

An example ORDC is depicted in Figure S2, which shows the decreasing ORDC penalty prices with increasing system reserve levels. The ORDC scarcity price is zero until the probability for not having sufficient capacity to meet the operating reserve requirement becomes nonzero. Then the price follows the curve until it plateaus at the MRR value with the corresponding maximum scarcity price (600 MW at $850/MWh in the EMIS-AS example in Figure S2).

Because of the above assumptions, operating reserve revenues from our modeling simulations are only non-zero for the products with ORDCs, which are Synchronous and Primary reserves in this study. All other operating reserve products consistently have zero or near-zero revenues because of their less-stringent scarcity assumptions and the assumed zero cost for providing operating reserves.

Table S2. Summary of operating reserve products

Operating Reserve Product	**Requirement**	**Response time (minutes)**	**Scarcity Pricing ($/MW)** low / base / high	**Notes**
Regulation ("Reg") Up	Method from (Ibanez et al., 2012)[a]	5	1002 / 4002 / 10,002	
Regulation ("Reg") Down	Method from (Ibanez et al., 2012)[a]	5	1001 / 4001 / 10,001	
Synchronous	100% of nameplate capacity of largest generator in system (PJM, 2020)[b]	10	1000* / 4000* / 10,000*	*Scarcity pricing switches from static values shown here to ORDC curve in scenarios with ORDC
Flexibility ("Flex") Up	Method from (Ibanez et al., 2012)[a]	20	999 / 3999 / 9,999	

Flexibility ("Flex") Down	Method from (Ibanez et al., 2012)[a]	20	998 / 3998 / 9,998	
Primary	150% of nameplate capacity of largest generator in system (PJM, 2020)[b]	30	997* / 3997* / 9,997*	*Scarcity pricing switches from static values shown here to ORDC curve in scenarios with ORDC

[a] Ibanez, E., Brinkman, G., Hummon, M., Lew, D., 2012. Solar Reserve Methodology for Renewable Energy Integration Studies Based on Sub-Hourly Variability Analysis: Preprint (No. NREL/CP-5500-56169). National Renewable Energy Lab. (NREL), Golden, CO (United States).

[b] PJM, 2020. PJM Day Ahead Reserve Requirements. PJM. Available: https://www.pjm.com/-/media/committees-groups/committees/oc/20191112/20191112-item-07-2020-dasr-requirement-update-reline.ashx

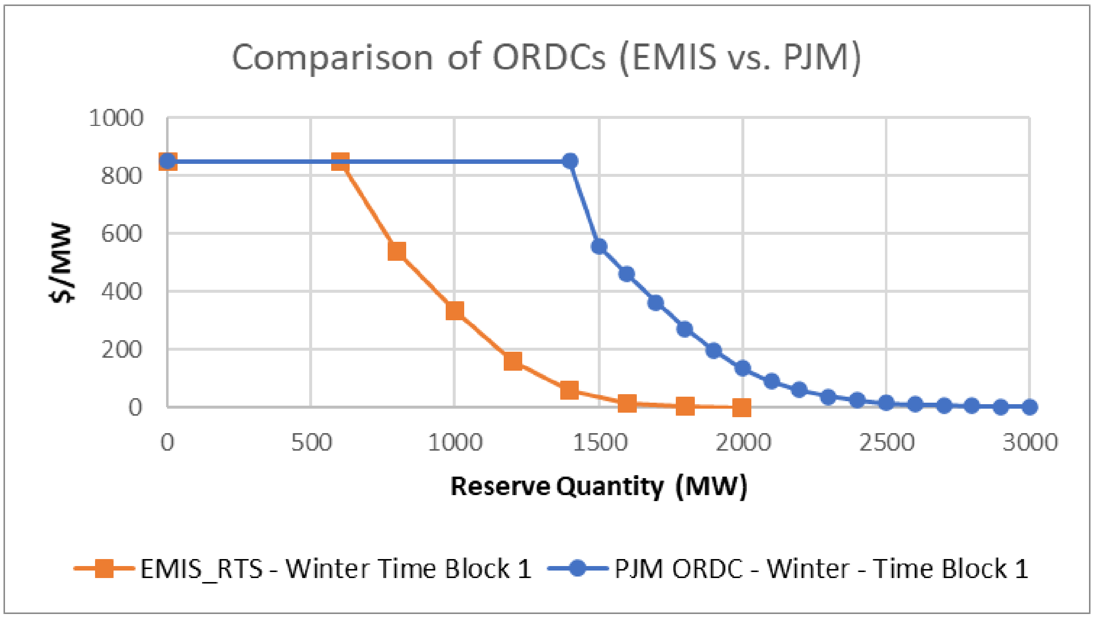

Figure S2. Example ORDC curve for winter (23:00 – 02:00) in comparison to the PJM curves. Note that the inflection points do not match because system sizes are different, but the slopes align well.

The second model enhancement is adding a new generator technology, RE-CT, which serves as a generic flexible combustion turbine (CT) generator that operates similar to a natural gas-fired CT (NGCT) but can be fueled by a range of potential renewable fuels, including biofuels, hydrogen, synthetic methane, among others (Cole et al., 2021). We assume the same operating parameters for the RE-CTs as NGCTs except for a fuel price of $20/MMBTU, 100% clean energy (i.e., eligible for the CEC market), and 103% capital cost of NGCTs.

The third model enhancement is adding a stylized inertia product that accounts for the rotating mass of traditional thermal generators and the fast frequency response (FFR) capability of inverter-based resources (IBRs), which include wind, solar, and batteries in this study. IBRs can provide FFR by rapidly changing their generation output – much faster than conventional generators – either by extracting kinetic energy from the rotating blades of wind generators or maintaining headroom (relative to the actual resource availability) of solar and battery resources so that generation can be increased (Denholm et al., 2021, 2019). While FFR is not a direct replacement for inertial response, it can, if coordinated properly, serve as a valuable service for maintaining system frequency.[1] We make the simplifying assumption that FFR can tradeoff equally with traditional rotating-mass inertial response because both ultimately contribute to this high-level system need of maintaining frequency at very short timescales. We assume inertial response can be provided by the online capacity of thermal generators based on the H-constant response rates in the IEEE RTS-GMLC data set and by the available headroom of IBRs based on response rates from the literature (Asmine et al., 2018; Khazaei et al., 2020; Zavadil et al., 2009). We also assume that the inertia requirement for the system scales to that of ERCOT's critical limit of 100 GW-s based on its corresponding peak load of 73.5GW (ERCOT, 2018). We allocate a portion of that requirement to our system each year as the peak load grows. We also assume an inertia scarcity price of $4000/MW.

The fourth model enhancement is updating the capacity credit methodology for wind, solar, and storage. Wind and solar already use an hourly load duration curve approximation method based on that used by NREL's Regional Energy Deployment System (ReEDS) model (Frew et al., 2017), but we now enable a static multiplier of the "default" values calculated with this method to enable lower or higher effective values for clearing the capacity market and contributing to the planning reserve margin. We also now extend this approach to a simplified version of the hourly-based methodology for battery storage currently used in ReEDS (Frazier et al., 2020), with the option to apply a post-process scaling up or down the default values from the hourly method. Each of these methods capture the declining value of capacity with increasing contributions levels from each resource due to their coincident nature. For storage, we calculate an average capacity credit of the existing system based on the ability of the existing storage capacity to reduce the peak net load given its storage duration. In this study, all storage is assumed to be 4-hour duration battery storage.

The fifth model enhancement is adding carbon pricing. We assume exogenously-defined carbon taxes that increase each year based on values from the ReEDS model (Caron et al., 2018). A summary of the values used are provided in Table S3. This tax is applied as an additional marginal cost for carbon-emitting resources.

Table S3. Carbon taxes for each simulation year

Year	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**	**2031**	**2032**	**2033**	**2034**	**2035**
Carbon Tax ($/tonne)	0	30	31.5	33.1	34.7	36.5	38.3	40.2	42.2	44.3	46.5	48.9	51.3	53.9	56.6

The sixth, and final, key model enhancement is implementing the restriction of some technologies from participating in the forward capacity market and provision of operating reserves. We apply a binary all-or-nothing eligibility of wind, solar, and battery storage for capacity market participation. When a given technology is excluded, we assume that this applies to both existing and new builds. This serves as a proxy for price floor offer rules, such as the Minimum Offer Price Rule that can effectively preclude these resources from clearing the capacity market, though the details of such rules are far more

[1] We note that FFR is typically classified as a type of primary frequency response (PFR), which helps to restore frequency within a few seconds and is usually provided by turbine governors (Denholm et al., 2019). As a generalization, PFR is a slower response than FFR, and FFR is slower than inertial response. PFR is distinctly different from regulation operating reserves, where the latter is provided by generators with automatic generation control that receive and respond to a signal from the system operator every few seconds to help maintain balance in system deviations between real-time market dispatch intervals (EPRI, 2019).

complex and nuanced than our simple approach here. Similarly, the capability of restricting operating reserve provision from wind, solar, and/or battery storage is also incorporated.

Additional Results

Impact of homogenous investor firms

Figure S3 compares new installed capacity between the scenario with homogenous firm characterization (Base_Hom) and the Base scenario (heterogenous firms) for each CET level. We see more new capacity deployed in the case with homogenous firms, particularly from capital-intensive technologies (natural gas-fired generators, solar, and batteries), but this trend is not evident for generation outcomes (Figure S4). The larger capacity in the homogenous firms (Base_Hom) scenarios is because all investors make the same, sometimes unknowingly redundant, investment decisions. Because new builds have discrete capacities, those new builds further yield collectively more capacity than needed.

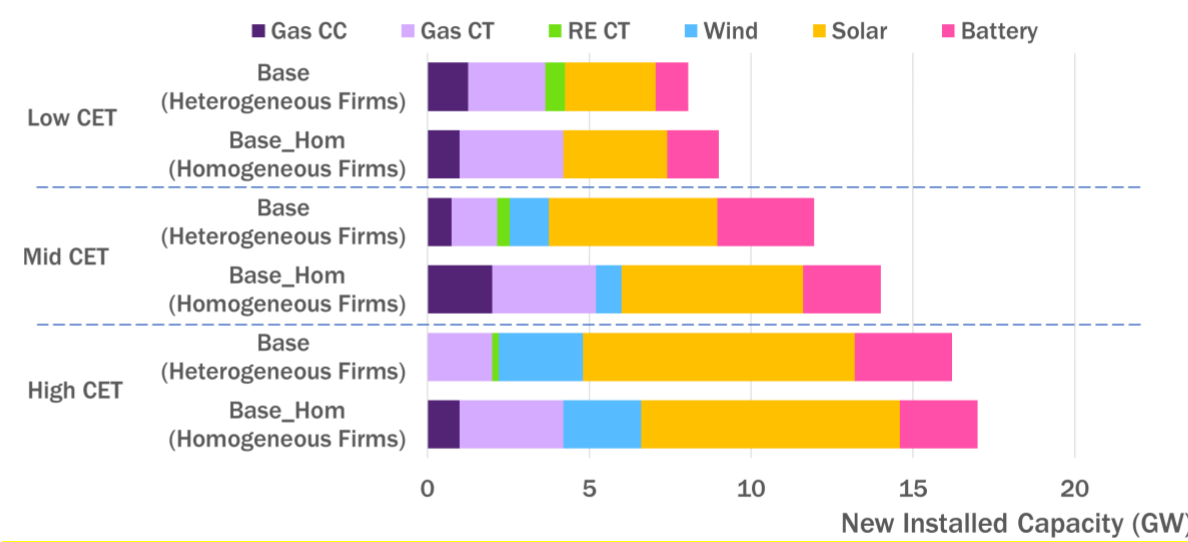

Figure S3. Total new capacity added during the simulation for the Base scenario and Base_Hom (with homogenous firms) in the 45%, 75%, and 100% CET scenarios.

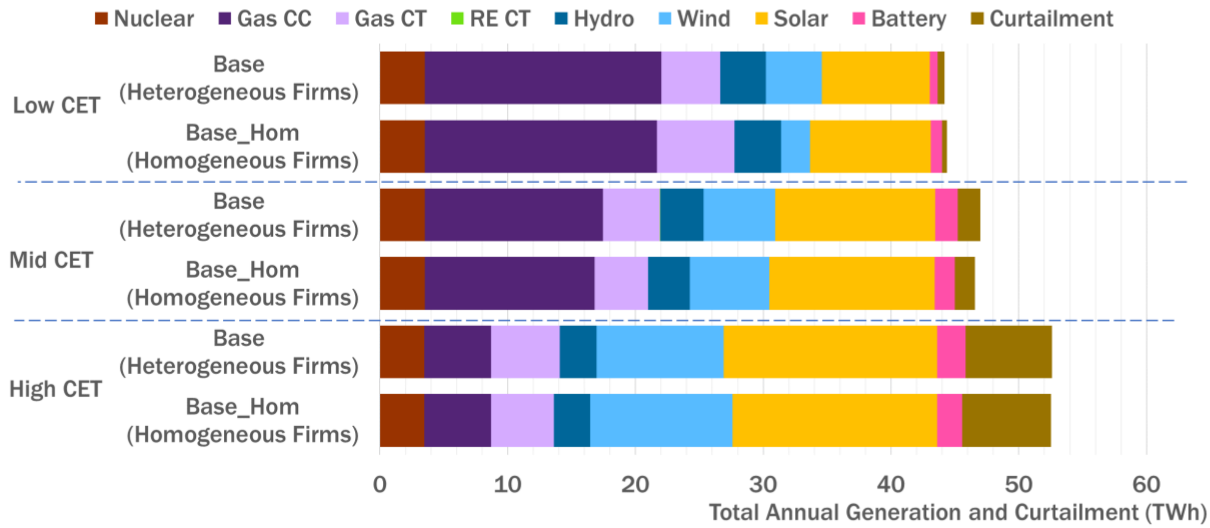

Figure S4. Total annual generation and Curtailment in the final simulation year (i.e., 2035) for the Base scenario and Base_Hom (with homogenous firms) in the 45%, 75%, and 100% CET scenarios.

Figure S5 shows the corresponding uniform profitability distribution across investor types in the Homogenous Firms scenarios, compared to the Base scenarios for different CET levels. While firms' profitability is identical in the homogenous scenario, the Large Utility has the highest overall investment and associated profitability because when heterogeneous firm characteristics are considered in the Base scenario.

The overbuilding trend observed in the Homogenous Firms scenarios and the higher profitability for larger firms in the Base scenarios aligns with existing literature (Anwar et al., 2022) and highlights the benefit of capturing the competitive interactions of heterogenous financing and risk profiles. The latter is a key value proposition of EMIS-AS over traditional expansion models that inherently assume a homogenous financing and risk parameters for the central planner.

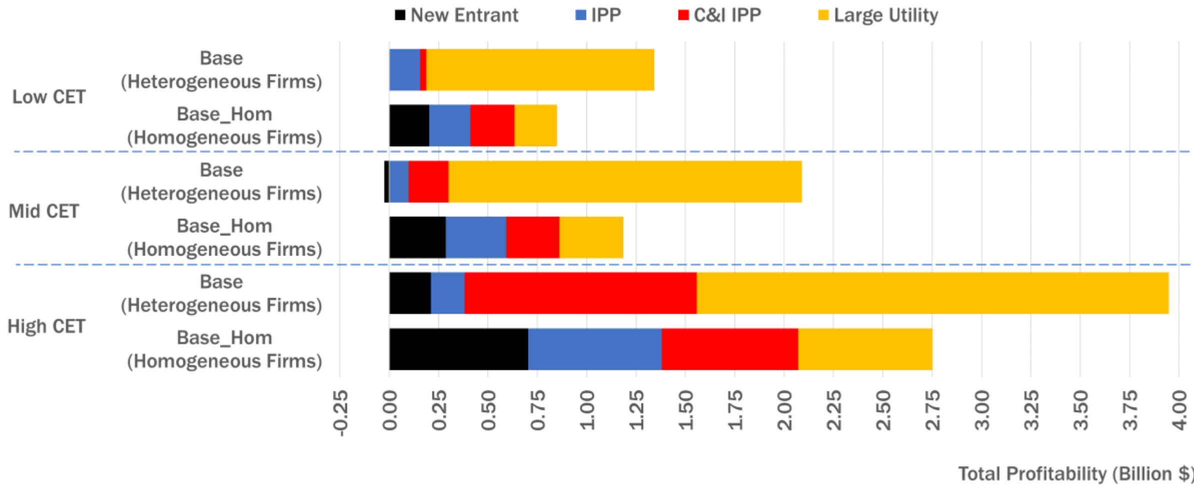

Figure S5. Total profitability of investor firms (across the 15-year simulation horizon) for the Base scenario and Base_Hom (with homogenous firms) in the 45%, 75%, and 100% CET scenarios.

Impact of operating reserve eligible rules on dispatch, reserve provision, and prices

These resource utilization trends can be better understood through an example dispatch period. Figure S6 shows an example day of July 13th in the final simulation year (i.e., 2035) at the High CET level. As we move from the far upper left panel where wind, solar, and batteries can all provide reserves (ORDC_Carbon_100) to the middle upper panel where wind and solar cannot provide reserves (No_VRE_Reserves_100), we see a 13% increase in gas-fired generation (driven by gas CCs), 16% reduction in wind generation, and a 6% increase in solar generation, all of which are consistent with the annual generation trends in Figure 26 in the main text. Because wind and solar cannot be used to provide operating reserves, we also see an increase in curtailment (3%). In the middle row of Figure S6, we see the total upward direction operating reserve provision (i.e., Synchronous, Primary, Flex Up, and Reg Up). When wind and solar cannot provide operating reserves (No_VRE_Reserves_100), there is a 33% reduction in gas-fired generator provision because the system can utilize available headroom from the RE-CTs, which have been built and committed to help satisfy the 100% CET. Batteries provide 45% more upward direction reserves in this scenario, as they have sufficient state of charge and zero marginal cost to provide low-cost reserves. As shown in the lower left and middle panels for these scenarios, energy prices generally remain below about $60/MWh, with prices falling to zero or near-zero in the middle of the day when solar is the marginal unit, and the weighted-average upward reserve provision price (using the upward direction reserve requirements as weights) remains at zero for all timesteps.

When we also prohibit batteries from providing operating reserves (third column in Figure S6), we see even more gas-fired generation (21%) relative to the ORDC_Carbon_100 scenario for this example day of July 13th. We also see 35% more curtailment because more gas generators are utilized to provided upward direction reserves (40% increase relative to the ORDC_Carbon_100 scenario), enabling 15% more wind to be utilized for energy production. Battery utilization is reduced by 62% because it no longer can provide operating reserves, and wind and solar can generate directly to the grid for most timesteps. However, the synergistic relationship between batteries and solar results in a 19% decrease in solar generation. We also see in the bottom right panel of Figure S6 that upward operating reserve prices (and in turn, energy prices) hit scarcity pricing levels in many timesteps, driven by an insufficient pool of eligible resources. This also results in a significantly lower upward reserve provision profile in the middle right panel, though we note that the total operating reserve requirements vary by scenario and year based on the system buildout and load profile for that year.

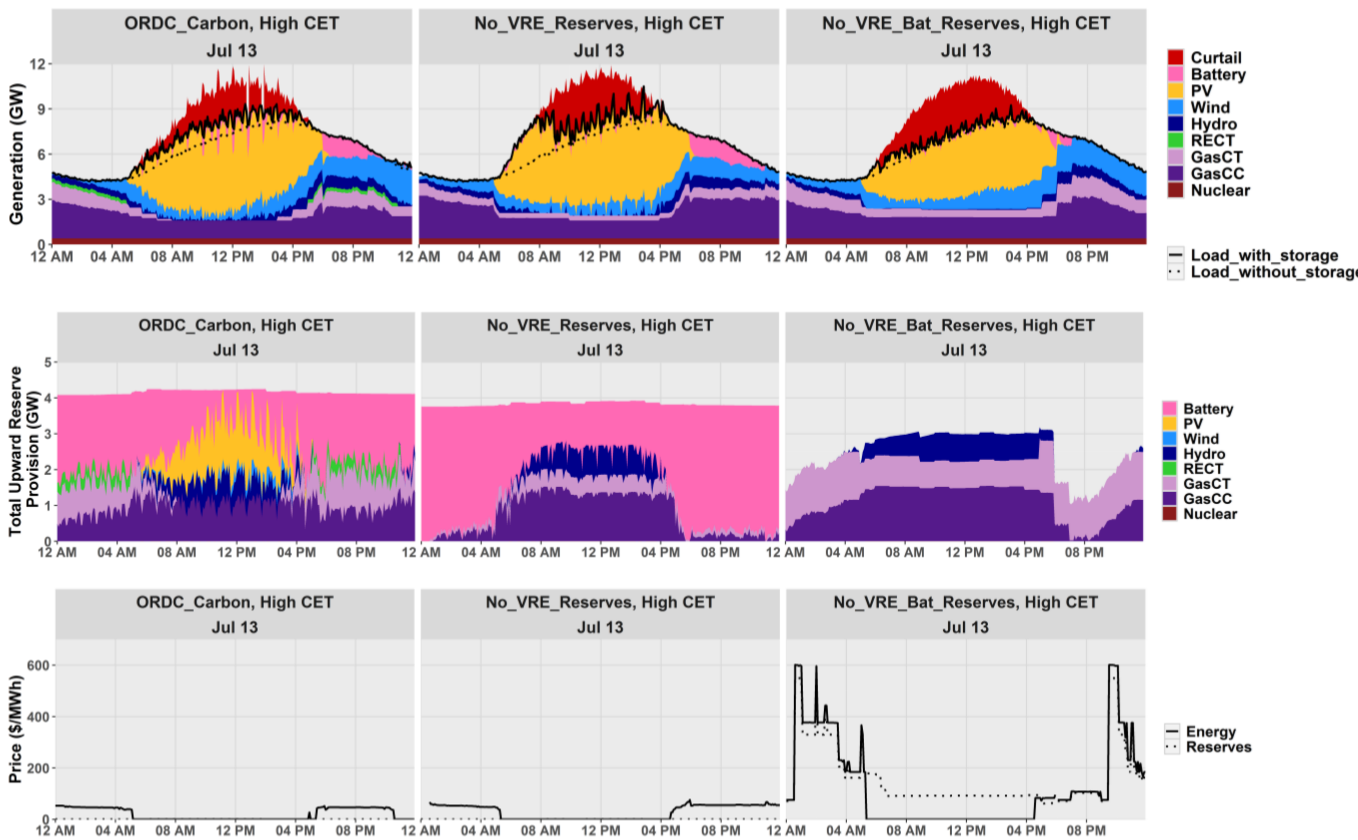

Figure S6. Generation, operating reserve provision, and corresponding prices for an example day in 2035 for the scenarios exploring VRE (wind and solar) and battery participation in operating reserve markets (all include ORDC and a carbon tax) for the 100% CET level. ORDC_Carbon allows VRE and batteries to provide operating reserves, No_VRE_Reserves does not allow VRE to provide operating reserves, and No_VRE_Bat_Reserves does not allow VRE or batteries to provide operating reserves, all else equal.

Additional Future Work

We expand here on an important modeling caveat mentioned in the main text that results in generation outcomes not always meeting the CET values established for each year, despite sufficient clean capacity being procured (see main text Section 3). This discrepancy is because of the stepwise nature of the modeling workflow of EMIS, where investment decisions are based on results from the GEP model (Step 1 in Figure S1), while generation outcomes are determined by the PCM (Step 5 in Figure S1). The GEP can ensure investment decisions technically can satisfy annual policy targets, such as the CET values enforced in this study. However, the current version of the PCM used in EMIS-AS cannot ensure the actual market-based operational outcomes meet those CET values, as the PCM only sees a handful of 5-minute operational timesteps at a time, rather than the full year. Furthermore, the current version of the GEP does not include unit commitment in its simplified operational representation, which can skew the expansion signals.

Future work could add unit commitment to the GEP and an annual clean energy accounting methodology to the PCM, for example through a nested allocation scheme. Future work could also explore strengthening the relationship between the carbon pricing and CET outcomes, for example through an endogenous auction-based carbon pricing scheme (e.g., carbon cap and trade). This would apply larger carbon prices – translated as larger marginal cost bids to the wholesale energy and operating reserve markets – for carbon-emitting resources when the emission cap nears its maximum annual allowance. In contrast, the current EMIS-AS formulation assumes exogenous carbon prices for simplicity. Ideally, any of these annual carbon or clean energy accounting methods would likely be coupled with an additional iteration between the GEP and PCM steps in EMIS-AS to enhance convergence in the pricing, investment, and dispatch outcomes. However, challenges could still arise from the lag time between the point of a given investment decision and operational availability.

This disconnect between investment and operational decisions observed at High CET levels also underscores the need for system planners and operators, as well as policy makers, to enforce mechanisms that maximize alignment between entry/exit decisions and operational outcomes that support both policy and technical requirements. Current clean energy standards in wholesale market areas generally rely on market signals through portfolio evolution (e.g., declining energy prices as more zero-marginal-cost renewables are deployed) and supplemental CEC prices (C2ES (Center for Climate and Energy Solutions), 2019). Various contractual mechanisms, such as power purchase agreements (PPAs) are also often used as means to track clean energy contributions. Cap and trade programs, such as the quarterly allowance auctions in California, also serve as a means to signal for cleaner energy technologies, and along with carbon pricing to prioritize dispatch of the lowest carbon electricity, have proven effective thus far (California Air Resources Board (CARB), 2021).

Future work could also continue to enhance the capabilities of EMIS-AS. This could involve several improvements including increasing the spatial resolution for allowing placement of new builds at a nodal level (compared to the zonal/regional level considered in this work), applying uncertainty to other parameters in addition to load growth (e.g., fuel prices, renewable generation availability), incorporating flexible demand in both planning and operational decisions, capturing the impacts of historical profitability outcomes on future investment decisions, and developing more-robust market product representations (e.g., operating reserve cost-based bids, nested operating reserve responses, regulation mileage payments, and/or bilateral contracts). In addition, currently EMIS-AS does not include any support mechanisms to assist generators when revenues fall short. This includes out-of-market payments, including uplift (or make-whole) payments or policy-based subsidies such as production tax credits. Future work could explore the impact of these payment mechanisms.

Full Set of Results for All Scenarios

Figure S7 – Figure S21 show the full set of outputs for each scenario and CET level. These include total new capacity built in the 15-year simulation, total 2035 annual system-wide generation, total market revenues normalized by the installed capacity and averaged across the 15 simulation years, total system costs across the 15-year simulation, and total investor firm profitability across the 15-year simulation.

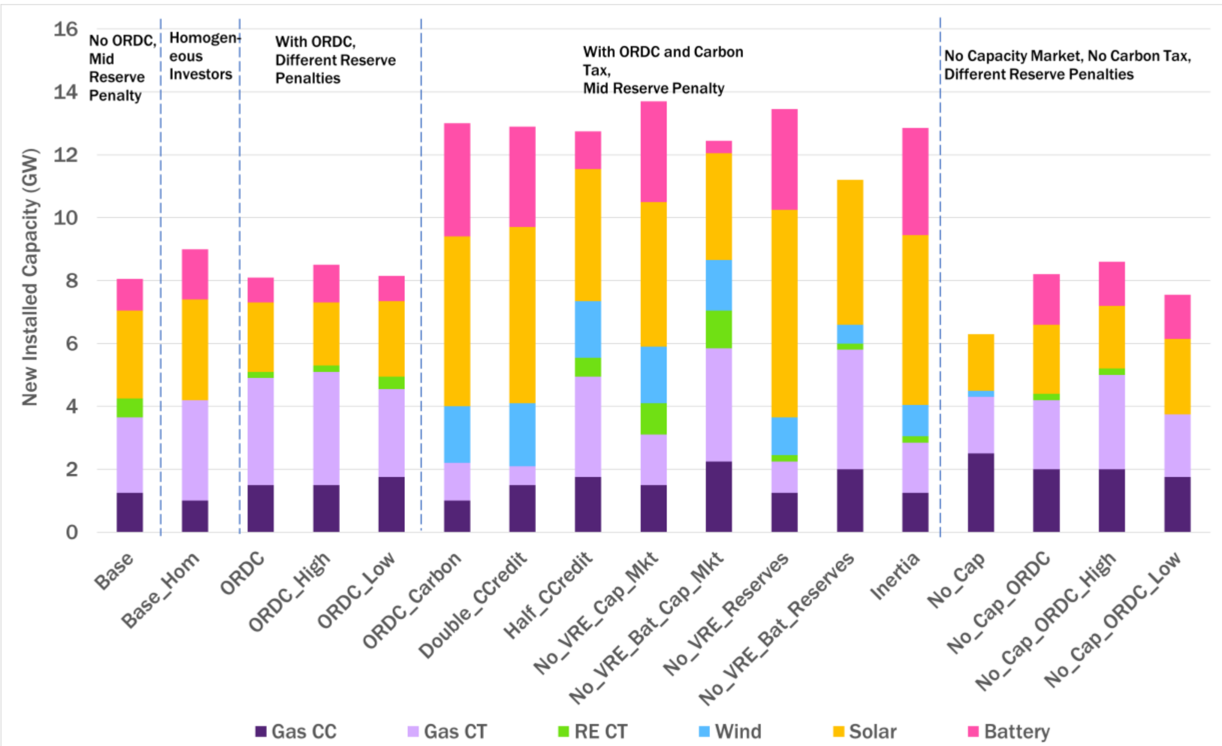

Figure S7. Total new capacity added during the simulation for all scenarios for the Low (45%) CET level.

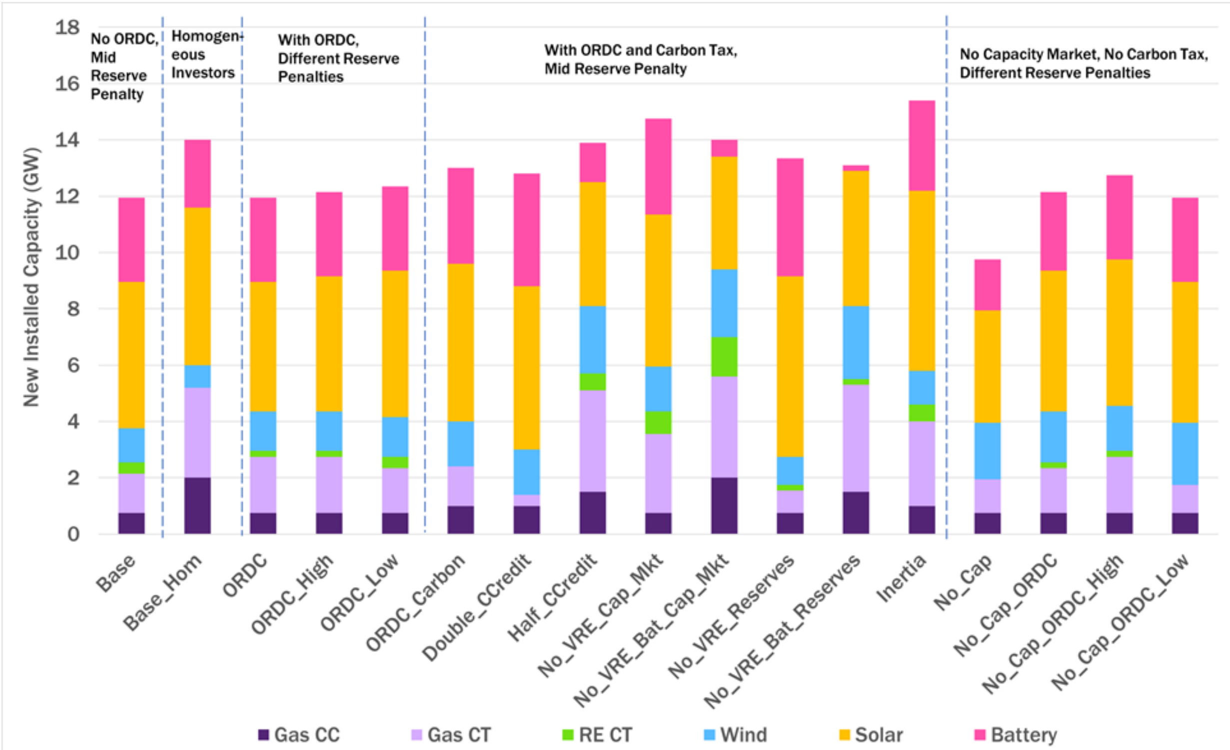

Figure S8. Total new capacity added during the simulation for all scenarios for the Mid (75%) CET level.

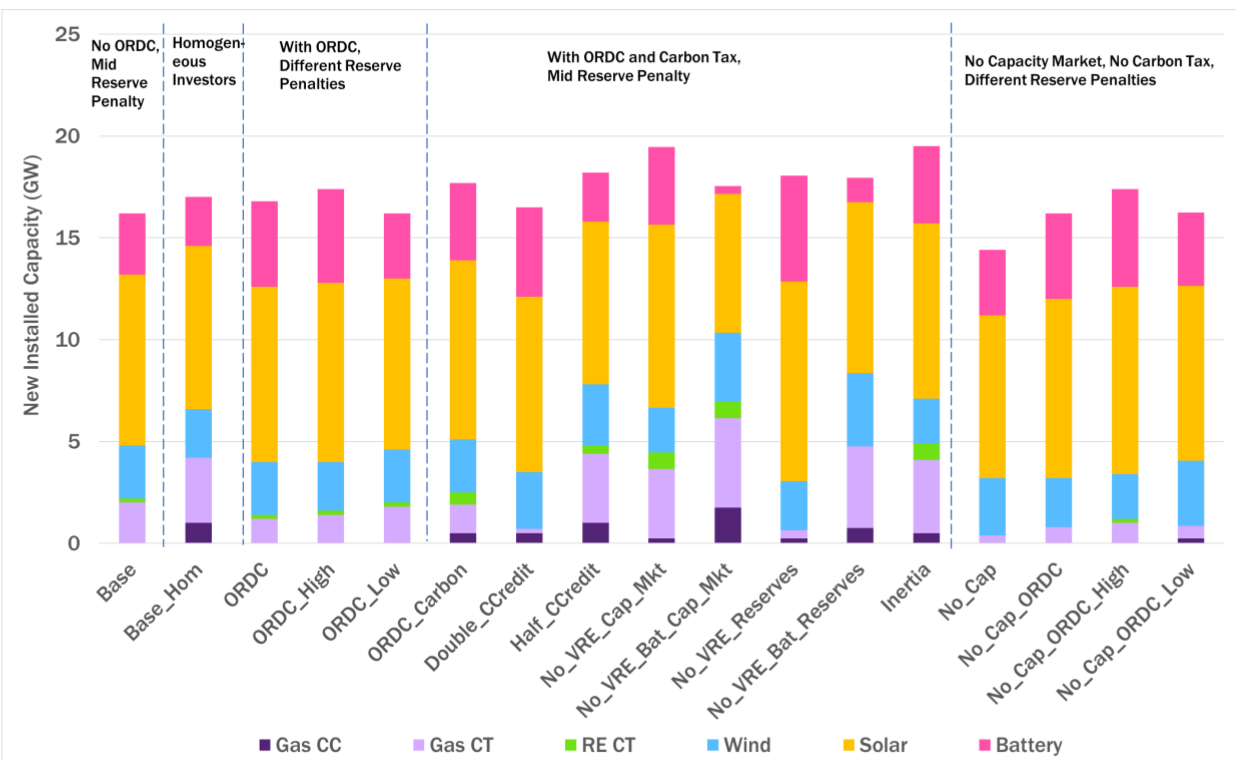

Figure S9. Total new capacity added during the simulation for all scenarios for the High (100%) CET level.

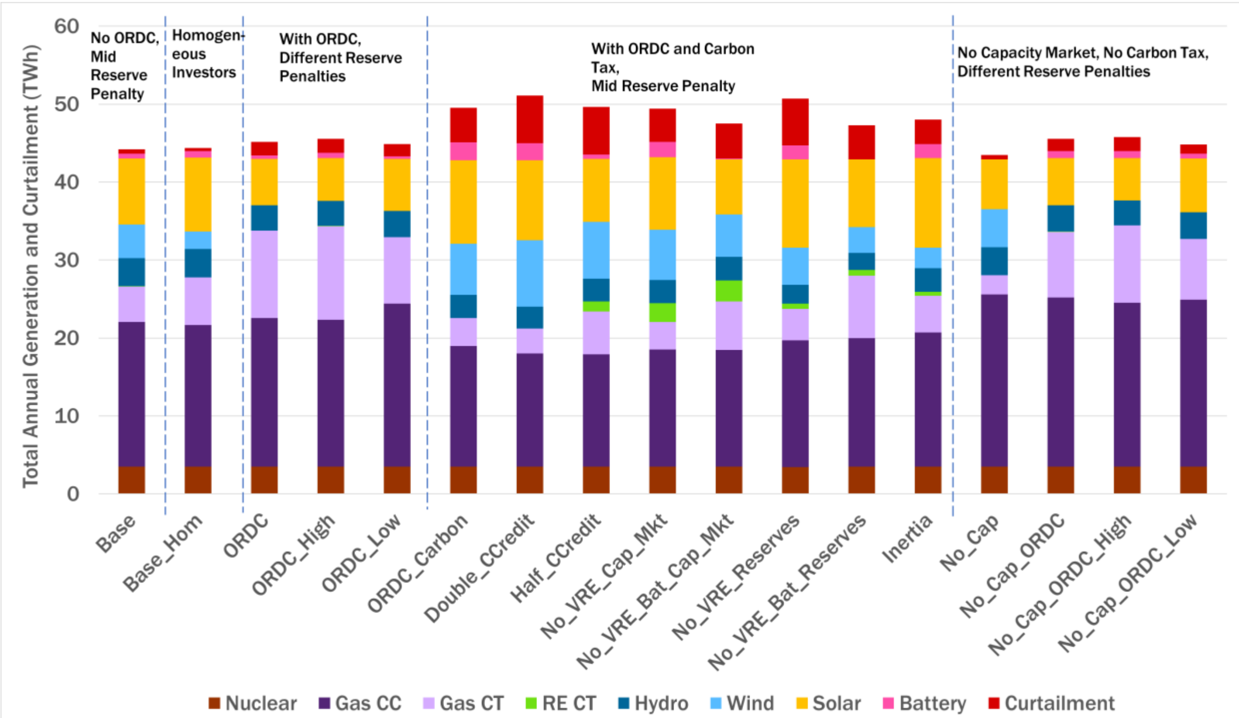

Figure S10. Total 2035 system-wide annual generation and curtailment for all scenarios for the Low (45%) CET level.

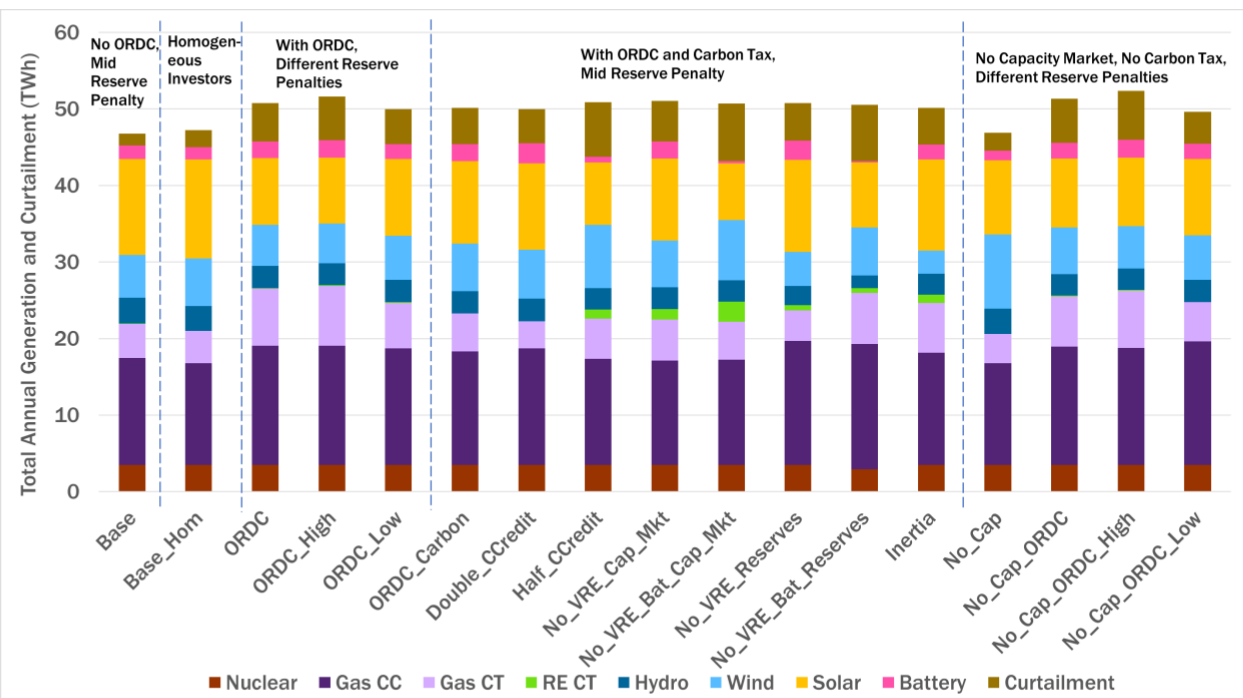

Figure S11. Total 2035 system-wide annual generation and curtailment for all scenarios for the Mid (75%) CET level.

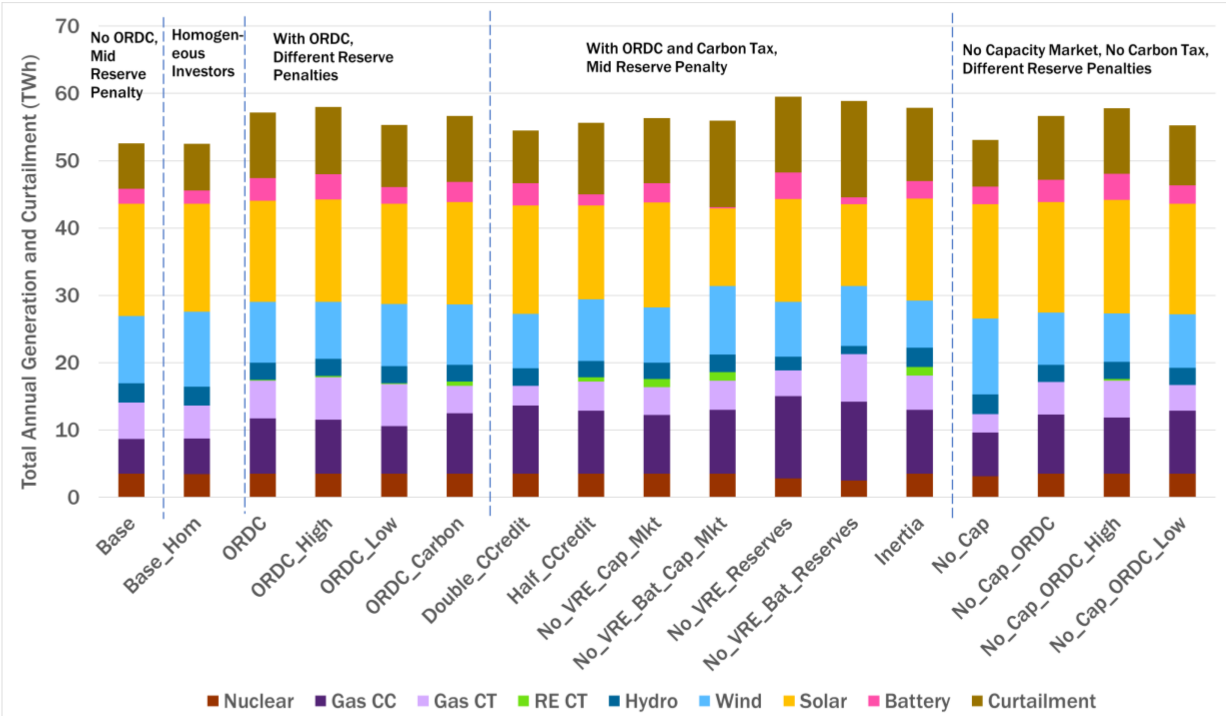

Figure S12. Total 2035 system-wide annual generation and curtailment for all scenarios for the High (100%) CET level.

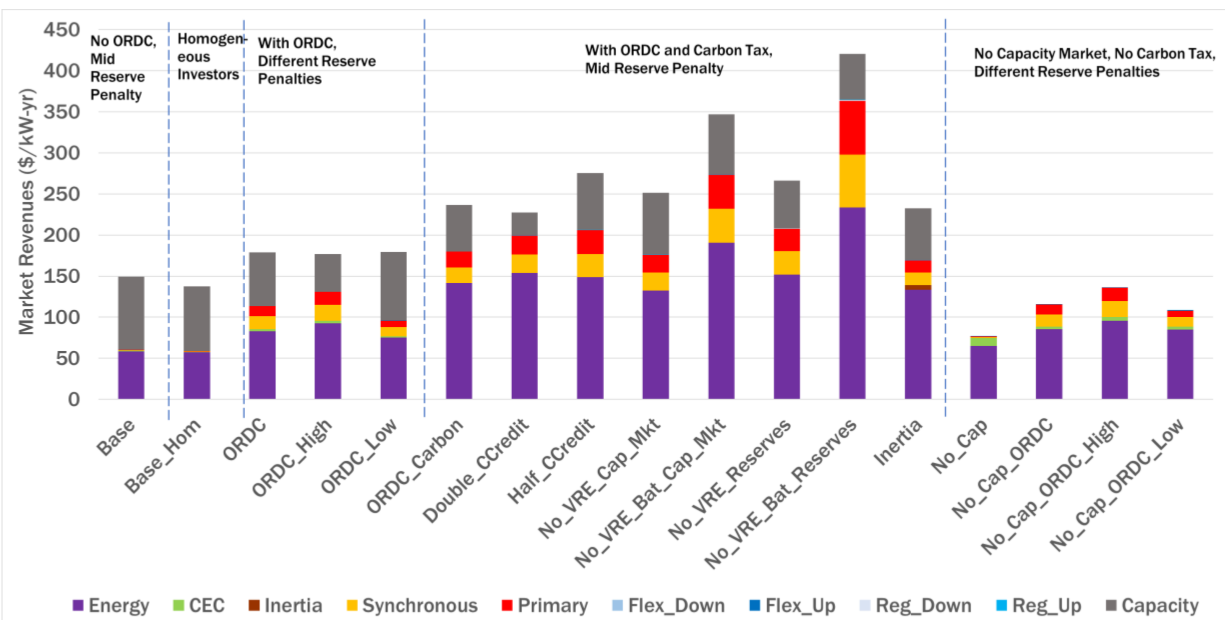

Figure S13. Annual market revenues (averaged across the 15-year simulation horizon) for all scenarios for the Low (45%) CET level.

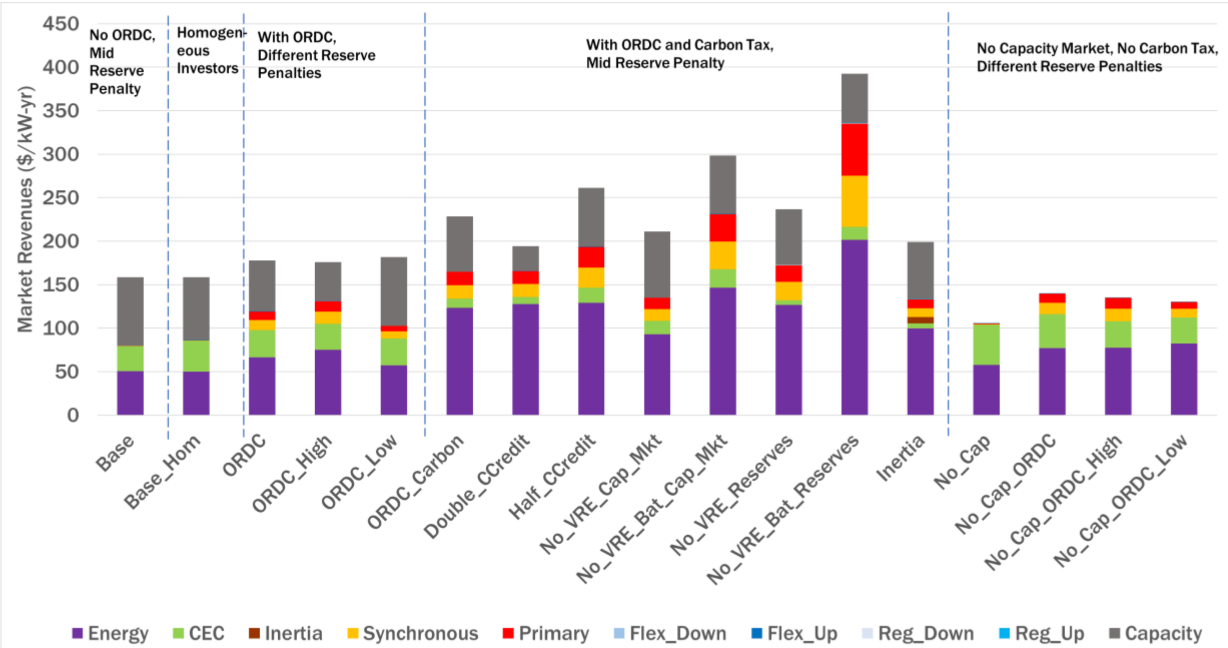

Figure S14. Annual market revenues (averaged across the 15-year simulation horizon) for all scenarios for the Mid (75%) CET level.

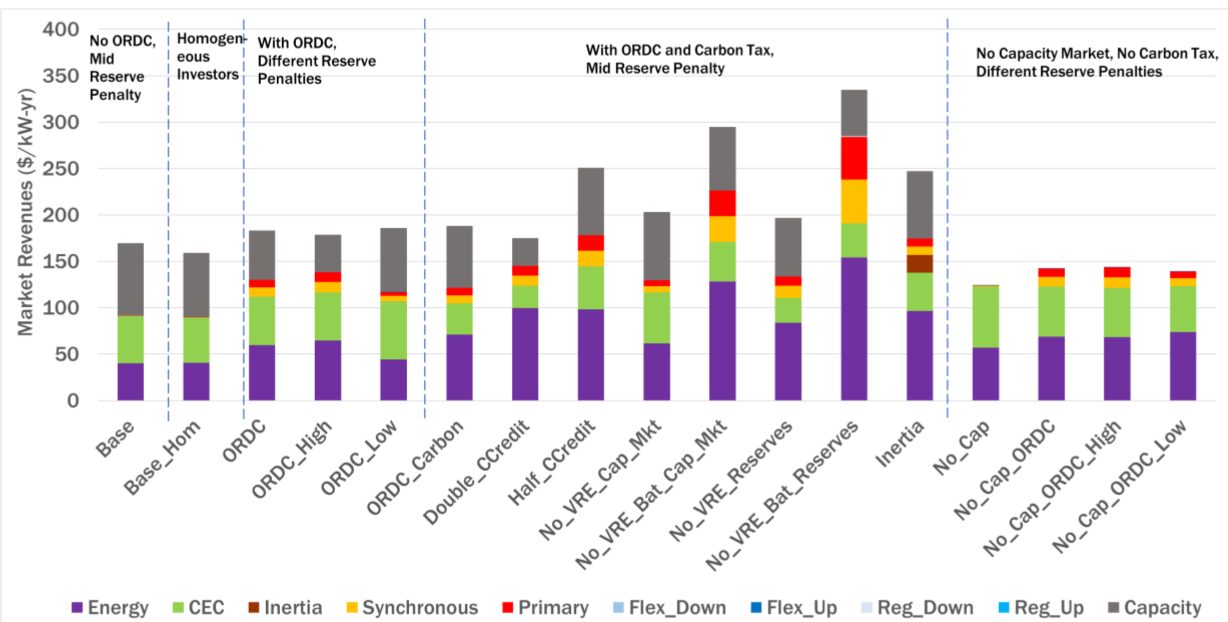

Figure S15. Annual market revenues (averaged across the 15-year simulation horizon) for all scenarios for the High (100%) CET level.

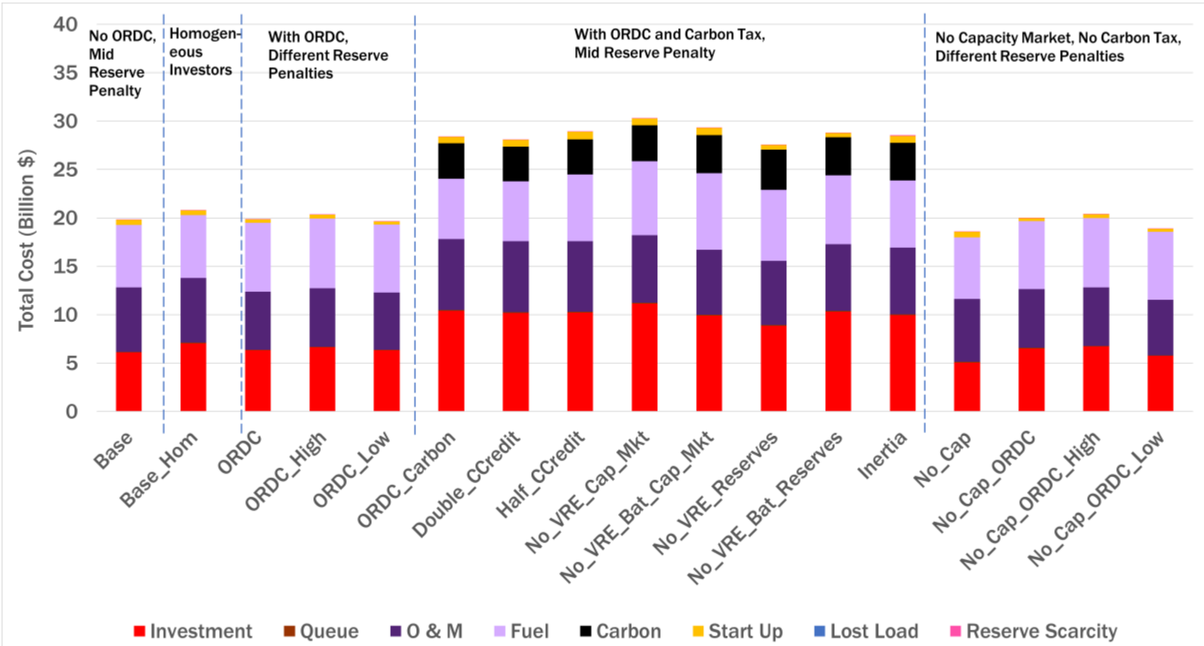

Figure 16. Total system costs (summed across the 15-year simulation horizon) for the Low (45%) CET level.

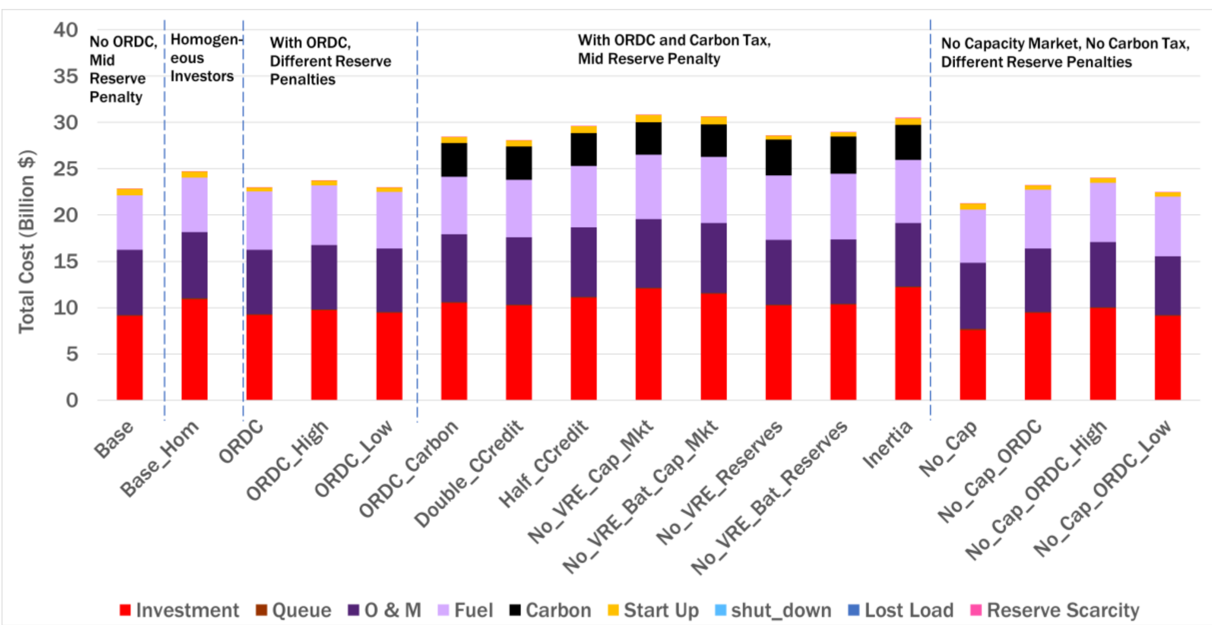

Figure S17. Total system costs (summed across the 15-year simulation horizon) for the Mid (75%) CET level.

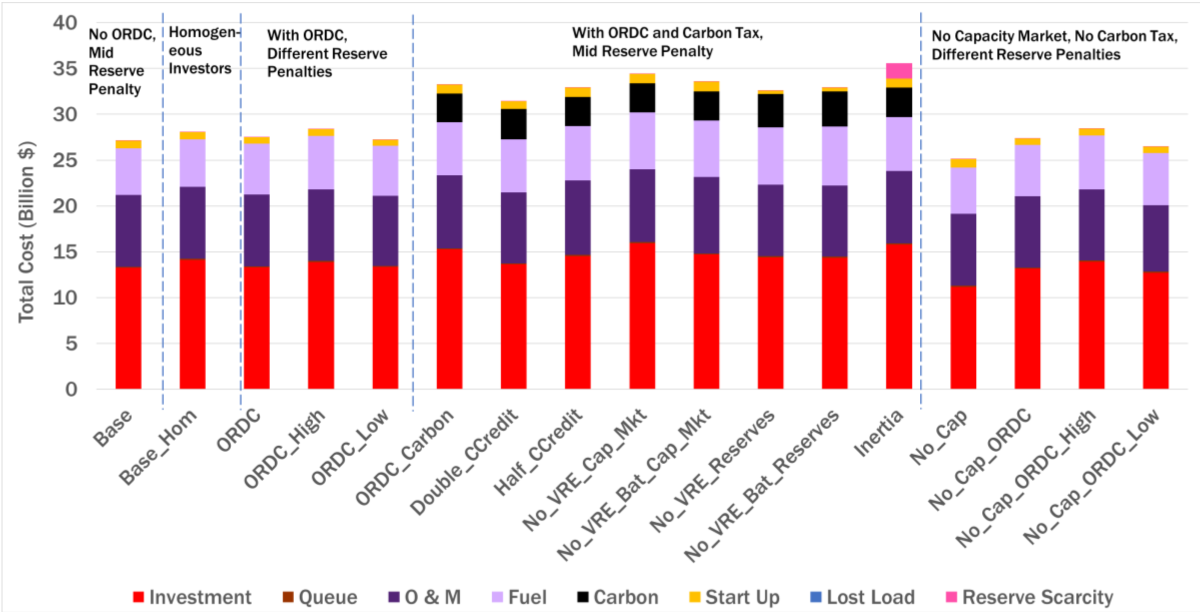

Figure S18. Total system costs (summed across the 15-year simulation horizon) for the High (100%) CET level.

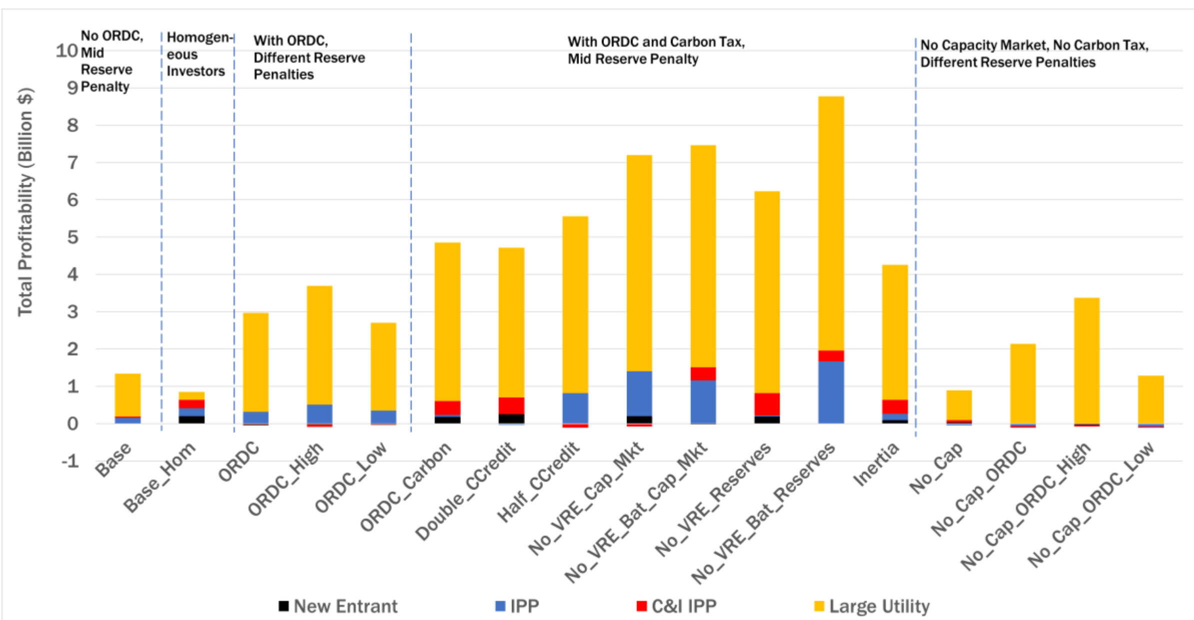

Figure S19. Total investor agent-level profitability (across the 15-year simulation horizon) for the Low (45%) CET level.

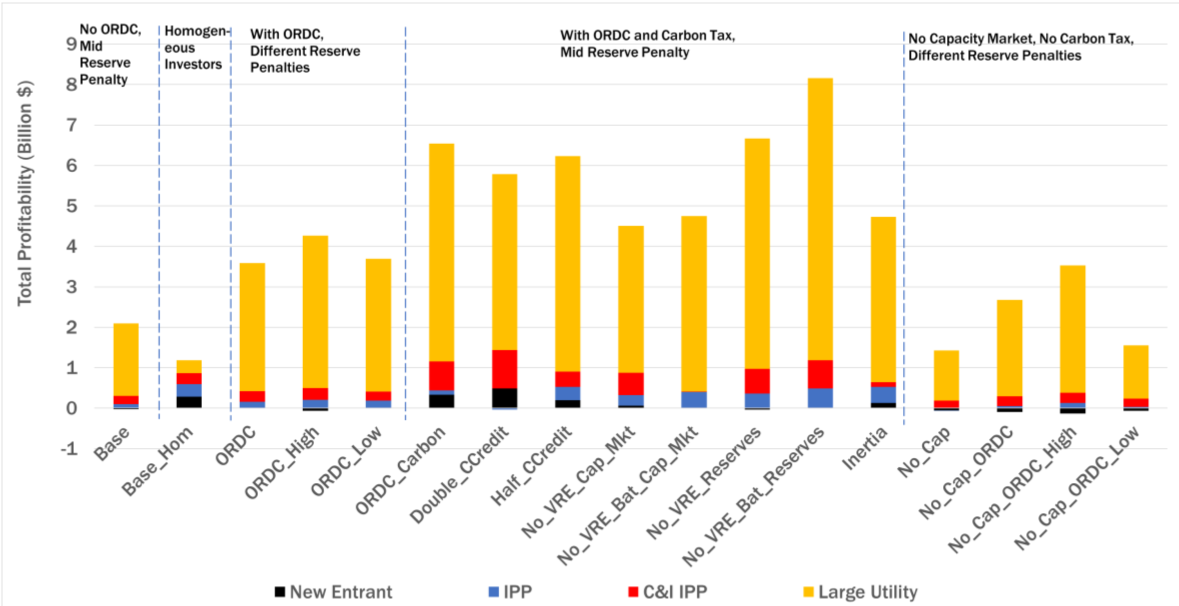

Figure S20. Total investor agent-level profitability (across the 15-year simulation horizon) for the Mid (75%) CET level.

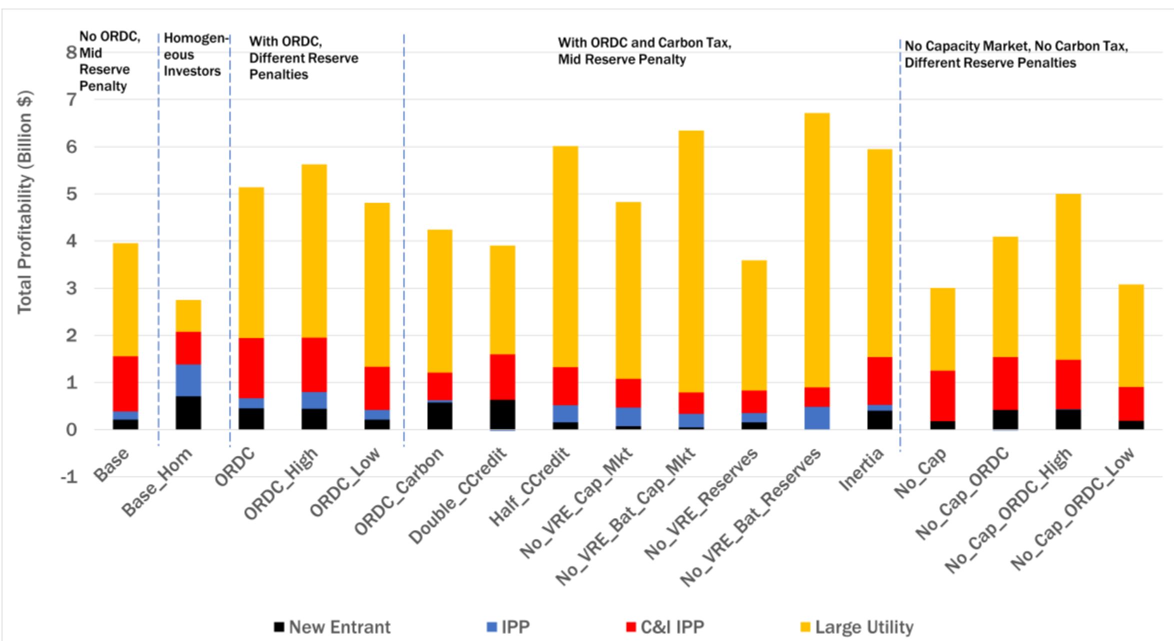

Figure S21. Total investor agent-level profitability (across the 15-year simulation horizon) for the High (100%) CET level.