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Price Formation and Grid Operation Impacts from Variable Renewable Energy Resources

September 2022

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*With special thanks to Wilfried Kabre for excellent research assistance.

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Summary

Variable renewable energy resources (VREs) are zero marginal cost resources that displace more expensive, emissions intensive generators in electricity dispatch, which can affect price formation, revenue sufficiency, reliability, market power mitigation, as well as market design and incentives for participation from other resources. In the literature that analyzes variable renewable energy resources (VRE) impacts on price formation processes, most studies focus on VRE impacts to short-term energy revenues through their locational marginal price effects in electricity markets. While the impacts of VREs on energy prices is a piece of the puzzle, it does not provide the whole picture. In well-functioning electricity markets, low energy prices could signal adequate capacity, or low energy prices could fail to accurately reflect the long-run scarcity value of electricity, affecting investment incentives for needed investment in new generation or maintenance of existing generation. Because of the nuances of low energy prices, in this review we provide an in-depth analysis of VRE impacts on revenue streams from energy, flexibility, and capacity markets, as well as other long-term contract mechanisms to provide a complete assessment of how VREs affect revenue sufficiency in electricity markets.

We identify several avenues through which VREs can impact price formation, including VRE impacts on short-term energy prices (day-ahead or real-time market price impacts), price volatility, ancillary service prices, and capacity or other long-term energy prices (capacity market prices or the impact of increasing VRE capacity on energy prices over time), all of which affect revenue sufficiency. Because VREs impact more than just prices in electricity markets, we also consider their impact on reliability, market power monitoring and mitigation, as well as state-level incentives, other economic trends and market design that both encourage and are adapting to increasing levels of VREs. Last, we consider how distributed energy resources (DERs) including demand response and storage technologies affect the integration of VREs and moderate their impacts. For each avenue, we examine recent electricity market trends and perform an in-depth survey of the literature to fully understand VRE impacts. We recommend several empirical models as well as questions for future research.

We find that increasing levels of VREs cause short-term energy prices, on average, to decline, which will be discussed in detail in Section 2.2.1. Zero marginal cost power producers displace power producers with higher fuel costs, reducing energy prices for all market participants. However, price declines vary temporally, geographically, and by the underlying resource portfolio, as the marginal generator displaced by the zero marginal cost resource and underlying market conditions determine the magnitude of price effects. Although short-term energy price impacts are well documented, we identify a need for additional research on the causal effect[1] of VREs, using more recent data from a broader selection of electricity markets, as VREs continue to increase across the United States; we recommend an empirical model to address this need. We also identify future research questions to further analyze the impact of VREs on short-term energy prices considering the impacts of generator outages, out-of-market actions, and transmission congestion. As a caveat, although our analysis of short-term energy prices in this review focuses on VRE impacts on wholesale market prices, emerging research has found that declines in wholesale prices due to VREs may not necessarily lead to declines in retail prices due to the allocation of fixed charges to retail customers (Borenstein et al. 2021), signifying VRE impacts on retail prices as an important area for future research.

[1] In this research, the term causal effect implies we are determining the cause-and-effect relationship of VREs on electricity prices, controlling for all other confounding factors, using econometric models.

Although the literature on how VREs impact short-term energy prices consistently finds average wholesale price declines during each studied period,[1] the literature on how VREs impact price volatility is less conclusive, as will be discussed in detail in Section 2.2.2. Some studies find increasing penetration of VREs increases temporal price volatility, while other studies are unable to show any significant evidence that the increasing share of VREs leads to high price volatility. Further, many factors may influence price volatility, including demand patterns, weather, and the availability of flexible generation. To parse out these effects, we identify future research questions and recommend an empirical model to better understand the impacts of VREs on price volatility.

Changes to price volatility due to VREs can create more periods with high prices as well as more periods with negative prices (Karandikar 2007; Schulueter 2010). Under these conditions, resources need to be aligned with where they are needed most to address short-term imbalances, a service typically accomplished with pricing of operating reserves or other ancillary services to incentivize resources to produce and sell power when and where it is needed most. The literature on price effects from VREs in ancillary service markets is less robust and nuanced than that on short-term energy price impacts, as will be discussed in more detail in Section 2.2.3; some research finds increasing levels of VREs reduce ancillary service prices through their price-reducing effect on energy market prices (Hirth and Ziegenhagen 2015; Gianfreda et al. 2016; Zarnikau et al. 2019), while other research finds that increasing levels of VREs increase ancillary service prices through raising demand for these services (Batalla-Bejerano and Trujillo-Baute 2016; Wiser et al. 2017; Di Cosmo and Valeri 2018). We identify future research questions and recommend an empirical model to parse out the demand- and supply-side effects of this problem, to determine the true impact of VREs on ancillary service prices.

Capacity market price impacts of VREs are also less well documented than short-term energy price impacts. Differences in market designs and mechanisms lead to large differences in capacity market clearing prices; however, limited research exists to understand how VREs impact capacity prices and payments, which will be discussed in detail in Section 2.2.4. Empirical analysis of long-term energy price impacts (the impact of increasing levels of VRE capacity on energy prices over time) in California points to increasing levels of VRE capacity decreasing daily prices, on average, but creating substantial decreases in midday prices while increasing shoulder hour prices. These findings imply that the economic viability of some resources may be undermined by VRE expansion. We recommend an empirical model to determine the impact of VREs on long-term energy prices and identify the need for further research into market-specific models to understand the impact of VREs on capacity market prices.

Because a resource's total revenues (and revenue sufficiency) consist of short-term revenues from wholesale energy and ancillary service markets, as well as long-term revenues from capacity payments, including from power purchase agreements (PPAs), we also examine the impact of PPAs for VREs on revenue sufficiency in Section 3.0. Because PPA data is limited in its availability, we conduct a case study on Sempra Energy, owner of San Diego Gas and Electric (SDG&E), to examine the impacts of PPAs, as well as other streams of revenue, to obtain a complete assessment of revenue sufficiency. We find that despite massive deployments of VREs in the California energy market, Sempra has been financially stable. However, some of Sempra's renewables plants have been extremely profitable, while others

[1] For example, (Owolabi et al. 2021) shows the negative impact of renewables on wholesale prices from 2014 to 2020. The wholesale price decline due to VREs has been documented in the literature from 2000 to 2020.

have operated at a loss, likely due to the prevailing prices at which PPAs were signed as well as corporate strategy. We point out a need for further research to understand how increasing levels of VREs affect PPAs and revenue sufficiency.

With respect to VRE impacts on market power monitoring and mitigation, we find consensus in the literature that although VREs tend to decrease average market prices, conventional generators can raise market prices in periods when little power from VREs is available, as will be discussed in detail in Section 4.0. Further, VREs can also affect congestion, creating opportunities for exercising market power. The ability to exercise market power can also affect long-term investment incentives. We identify a need for further research on the impacts of VREs on market power, as opportunities to exercise market power vary temporally and spatially with VRE production.

Various federal- and state-level policies encourage additional VRE investment. Empirical research on state-level renewable resource policies has found mixed results on their effect of encouraging deployment of VRE generation and emissions impacts, but generally concludes that these policies raise electricity prices, as will be discussed in detail in Section 5.0. Less empirical work has focused on state-by-state impacts of regional climate policies or regime changes, where we characterize regime changes as policies requiring significant changes to the underlying resource mix (e.g., Washington state will eliminate coal generation by December 31, 2025, as a requirement of the Washington Clean Energy Transformation Act—SB 5116 (2019)—we would consider such a change a regime change). We recommend an empirical methodology to examine state-level climate-related policies and regime changes to understand their impact on price formation and revenue sufficiency. As the ultimate goal of climate-related policies is to reduce greenhouse gas emissions, we also review the literature on actual emissions offsets from VREs, finding that emissions reductions depend on the marginal generator displaced by the VRE resource. We recommend an empirical model to understand how continued increases in VREs affect emissions across electricity markets.

Market designs are changing to accommodate the operational and financial challenges of increasing levels of VREs. As market designs continue to evolve to integrate VREs, climate impacts will be determined by the effective resource mix incentivized to participate in the market. However, as we transition to a zero marginal cost future with increasing amounts of VREs, emissions impacts may become less of a concern, replaced by new challenges in price formation, revenue sufficiency, reliability, and market power mitigation. The extent to which flexible demand will ameliorate these concerns remains open question. We survey the literature to understand how DERs, including demand response and energy storage technologies, can address or are already addressing the challenges introduced by VREs in Section 6.0. We find that most of these resources remain limited in their deployment due to barriers to adoption, economics, and other reasons, but theoretical research and case studies point to the ability of these resources to reduce energy prices, price volatility, and peak load, as well as mitigate market power.

Acknowledgments

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Acronyms and Abbreviations

AR	Autoregressive
ARCH	Autoregressive conditional heteroskedasticity
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
BRA	Base Residual Auction
CAISO	California Independent System Operator
CES	clean energy standard
CPUC	California Public Utilities Commission
DER	distributed energy resource
DSIRE	Database of State Incentives for Renewables & Efficiency
EGARCH	exponential generalized autoregressive conditional heteroskedasticity
EIA	Energy Information Administration
EIM	Energy Imbalance Market
ELCC	Effective Load Carrying Capability
EQR	Electronic Quarterly Reports
ERCOT	Electric Reliability Council of Texas
FERC	Federal Energy Regulatory Commission
GARCH	generalized autoregressive conditional heteroskedasticity
GJR	Glosten-Jagannathan-Runkle
GW	gigawatt
HCAP	high-system-wide-offer cap
IOU	Investor owned utility
IPP	Independent power producers
LCOE	Levelized cost of energy
LMP	Locational marginal pricing
LOLE	loss of load expectation
LOLP	loss of load probability
MIDAS	Missed data sampling
MISO	Midcontinent Independent System Operator
NERC	North American Electric Reliability Corporation
NYISO	New York Independent System Operator
ORDC	Operating reserve demand curve
PPA	Power purchase agreements
PUCT	Public Utilities Commission of Texas
PV	photovoltaic
RPS	renewable portfolio standard

RTM	real-time market
SARIMA	Seasonal autoregressive integrated moving average
SDG&E	San Diego Gas and Electric
SPP	Southwest Power Pool
VOLL	Value-of-lost-load
VRE	Variable renewable energy resources

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1.0 Introduction

Increasing amounts of variable renewable energy resources (VREs) impact electricity markets and their operation. VREs are intermittent, zero marginal cost resources that tend to displace emissions-intensive generators in electricity dispatch, reducing emissions but impacting price formation, revenue sufficiency, reliability, and market power mitigation processes of electricity markets. However, VREs are not the only factor that affects operational and financial challenges in electricity markets. Changing fuel prices, changing resource mixes, and different electricity market designs and regulatory policies all factor into the challenges both electricity market participants and operators face in today's electricity markets.

With this in-depth examination of electricity markets and related literature review, we aim to provide information on key challenges of market design and operation for successful integration of large amounts of zero marginal cost resources. We have identified several areas, including the impact of VREs on price formation, revenue sufficiency, reliability, market power monitoring, and mitigation, as well as how state-level incentives and market design impact VREs and these challenges, and how increased participation from distributed energy resources (DERs), including demand response and energy storage technologies could affect these challenges.

With each key challenge, we examine recent trends in electricity markets and survey the literature to answer the following question: What is the extent of the challenge and how has it evolved over time? We first conduct a thorough review of ongoing challenges in electricity markets to understand the problem and review the empirical literature to capture important findings on how VREs, specifically, impact the problem. From this review, we highlight metrics that are important to understanding VRE integration and how market designs and outcomes are evolving with increasing levels of VREs. We recommend several empirical models for future research to determine the impact of VREs on these identified challenges with the continuing increase in VRE penetration.

Our approach to understanding each challenge (price formation, revenue sufficiency, reliability, market power monitoring and mitigation, state-level incentives, other economic trends and market design, and the impact of DERs, including demand response and storage technologies) follows a general structure of examining the wholesale markets and existing literature to understand relevant trends. Because there are other factors aside from VREs that contribute to these challenges, we conduct an empirical evaluation or case study to understand how VREs specifically contribute to each challenge we have identified. We develop empirical models and questions for future research to determine the effect of increasing levels of VREs on electricity markets. In summary, our identified challenges from increasing levels of VREs, approach to address each of these challenges, and roadmap to the rest of the paper is detailed in Table 1.

Table 1. Approach to Address Each Challenge

Identified Challenge	Approach Developed to Address Challenge
VRE Impacts on Price Formation (Section 2.0)	Conduct an examination of relevant price formation trends from wholesale markets and related literature (Section 2.1) Because price formation also impacts reliability, conduct an examination of relevant reliability trends from wholesale markets and related literature (Section 2.1.1)

Identified Challenge	Approach Developed to Address Challenge

	Review the empirical literature to understand VRE impacts on price formation (Section 2.2)
	• Short-term energy price impacts (Section 2.2.1)
	    – Literature review (Section 2.2.1.1)
	    – Recommend modeling approach and identify questions for future research (Section 2.2.1.2)
	• Volatility price impacts (Section 2.2.2)
	    – Literature review (Section 2.2.2.1)
	    – Identify common determinants of volatility in electricity markets (Section 2.2.2.2)
	    – Review volatility modeling approaches (Section 2.2.2.3)
	    – Recommend modeling approach and identify questions for future research (Section 2.2.2.4)
	• Ancillary service price impacts (Section 2.2.3)
	    – Literature review (Section 2.2.3.1)
	    – Recommend modeling approach and identify questions for future research (Section 2.2.3.2)
	• Capacity price impacts (Section 2.2.4)
	    – Literature review (Section 2.2.4.1)
	    – Recommend modeling approach and identify questions for future research (Section 2.2.4.2)

VRE Impacts on Revenue Sufficiency (Section 3.0)	Conduct an examination of relevant revenue sufficiency trends from wholesale markets and related literature (Section 3.1) Conduct a case study on Sempra Energy to under VRE impacts on revenue sufficiency, which includes an examination of VRE PPA revenues (Section 3.2) • Provide an overview of common electricity generator ownership models (Section 3.2.1) • Summarize methods for examining changes to revenue for utilities to form an annual picture of revenue stemming from generators (Section 3.2.2) • Conduct case study on Sempra Energy (Section 3.2.3)
Market Power Monitoring and Mitigation (Section 4.0)	Conduct an examination of market power trends from wholesale markets and related literature (Section 4.1) Review the empirical literature to understand VRE impacts on market power (Section 4.2)
Impact of Incentives, Economic Trends, and Other Designs (Section 5.0)	Conduct an examination of state-level incentives, other economic trends, and market design from wholesale markets (Section 5.1) Review the empirical literature to understand VRE impacts on state-level incentives (Section 5.2.1), emissions (Section 5.2.2), and market design (Section 5.2.3)
Impact of DERs, Demand Response and Storage Technologies (Section 6.0)	Conduct an examination of market trends and empirical literature for demand response (Section 6.1), energy storage (Section 6.2), and consider what these technologies mean for the future of the electric grid (Section 6.3)

2.0 Price Formation

2.1 Background and Relevant Trends

While increasing amounts of electricity production from wind and solar resources are beneficial to the environment, they create specific challenges for price formation in electricity markets. When the wind blows or the sun shines, these resources can produce power at zero marginal cost—wind or sun are freely available. In today's electricity markets, electricity resources are dispatched in merit order. When resources are bid into an electricity market, their supply offers are stacked in ascending order by marginal cost (the biggest component of which is fuel cost). Figure 1 displays the merit-order dispatch curve for the New York Independent System Operator (NYISO) portfolio of resources from 2020. Zero marginal cost resources, such as wind power in NYISO, are dispatched first, with more expensive fossil-fuel-fired resources dispatched according to their increasing marginal cost to meet electricity demand.

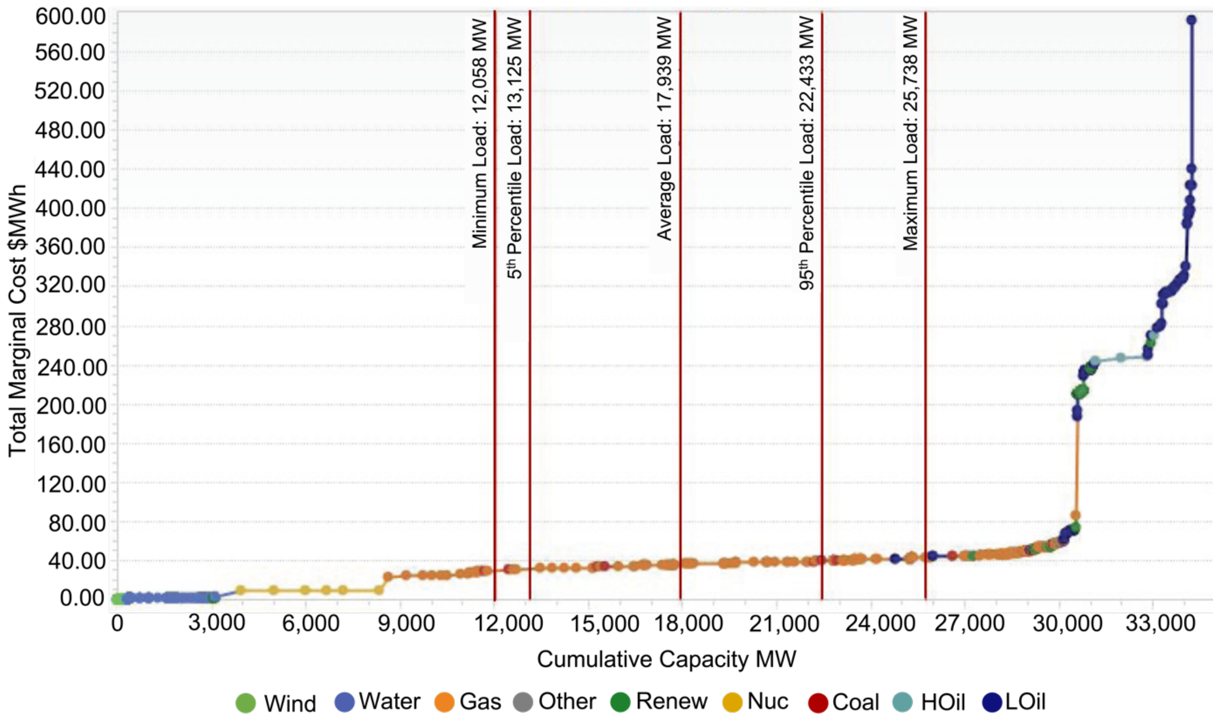

Figure 1. Market Supply Curve for NYISO. Source: FERC 2020.

The effect of increasing amounts of zero marginal cost VREs is to shift the dispatch curve to the right, lowering wholesale electricity prices, as shown in Figure 2 from 2010 to 2016 for PJM Interconnection's (PJM's) average supply curve by offer price. This is known as the merit-order effect (Sensfuß et al. 2008). The merit-order effect for PJM is particularly noticeable from 120,000 MW to 150,000 MW of load, the range in which peak load levels typically occur in the summer and winter.

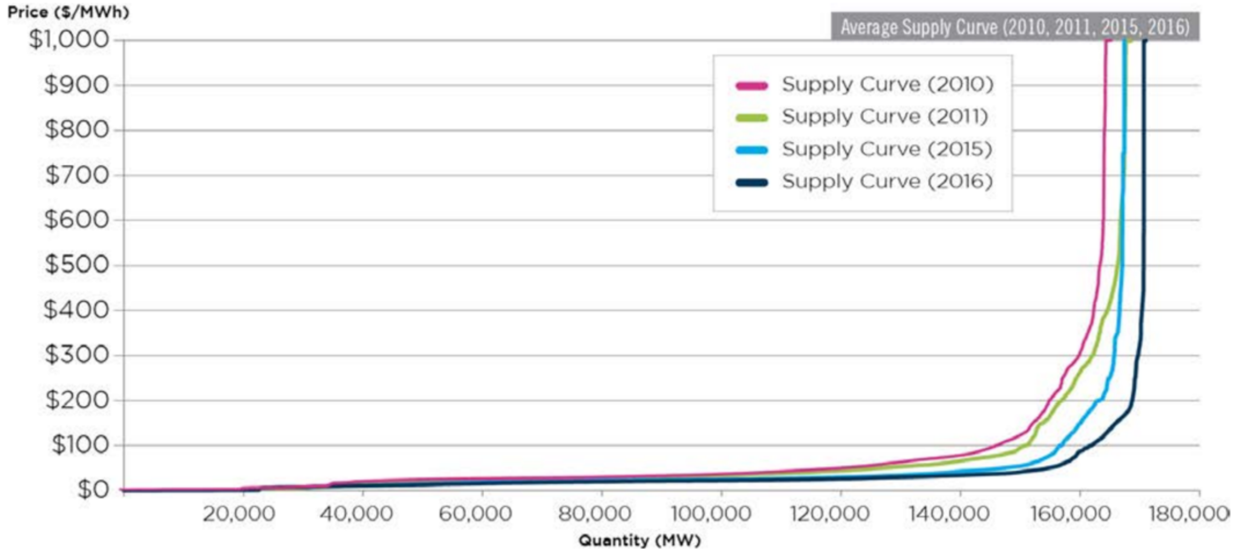

Figure 2. Supply Curve for PJM (2010, 2011, 2015, 2016). Source: PJM 2017.

Due in part to increasing amounts of VREs, declining natural gas prices from 2008 until the end of 2020 (after which we start to see an uptick), as shown in Figure 3, and other factors, wholesale electricity prices generally exhibit a downward trend over time.

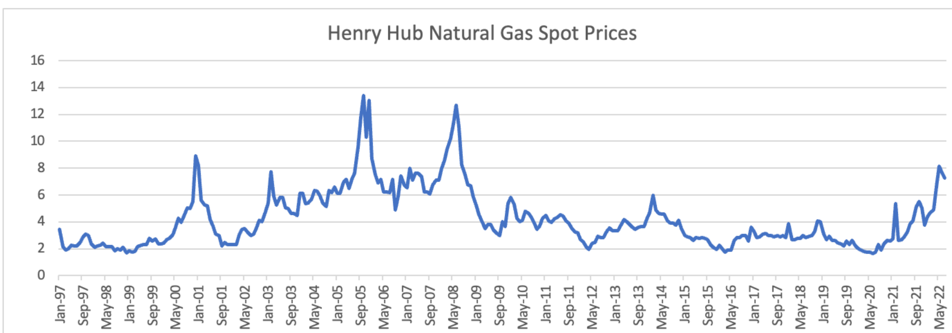

Figure 3. Monthly Henry Hub Natural Gas Spot Prices. Source: EIA 2022a.

Figure 4 depicts average wholesale electricity prices across ISOs in the United States from 2012 to 2020.

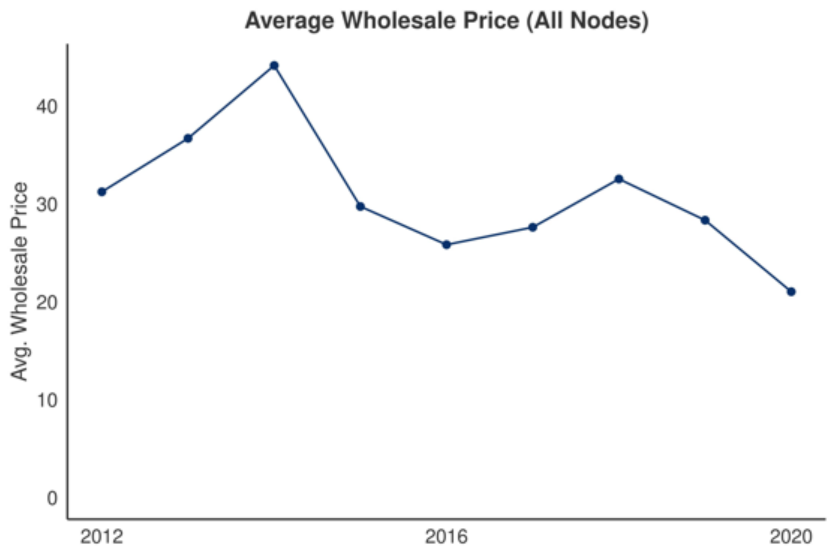

Figure 4. Average ISO Wholesale Electricity Prices. Source: Lawrence Berkeley National Lab 2022.

When demand levels are relatively low, or there is transmission congestion, high power production from VREs can even create negative prices, meaning power producers must pay load serving entities to consume more power. Renewable generators can earn renewable energy credits or tax credits that enable negative bids, while for other generator types, limited ramping flexibility and self-scheduled out-of-market commitments may also make negative bids optimal (Seel et al. 2021). As an example, as shown in Figure 5, which displays the hourly frequency of negative 5-minute prices by year in California Independent System Operator (CAISO), the high frequency of negative prices in 2017 was attributed to additional installed renewable capacity and additional generation from hydro resources, with negative prices occurring between February through mid-June during the midday hours when solar generation was greatest and demand was seasonally mild (CAISO 2017). The frequency of negative prices in 2019 was higher than in 2018 due to increased hydroelectric generation and lower demand in 2019, with most negative prices occurring due to solar resources bidding negative between February and June when hydroelectric generation peaked (CAISO 2019). Both 2019 and 2020 experienced a similar frequency of negative prices, with most negative pricing events occurring during midday when solar generation was high, and demand was low. However, 2020 had more negative pricing events between 9:00 a.m. and 11:00 a.m., likely due to decreases in demand from COVID-19 (CAISO 2020). It is clear from Figure 5 that the frequency of negative pricing occurs when solar power production is online in CAISO, but exactly how much VREs contribute to negative pricing needs to be disentangled from other factors, such as demand, hydroelectric production, transmission congestion, and the footprint of the market for addressing energy imbalances.

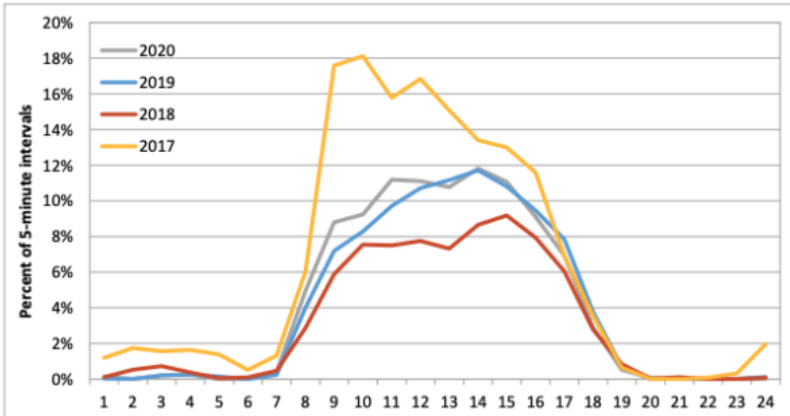

Figure 5. Hourly Frequency of Negative 5-Minute Prices by Year. Source: CAISO (2020).

Figure 6 shows the frequency of negative real-time wholesale electricity prices at the seven organized wholesale markets in the United States in 2020. Negative real-time hourly wholesale prices occurred in about 4% of all hours and wholesale market nodes (out of >50,000 nodes) across the United States. Negative prices are not distributed evenly across space. For example, negative prices are relatively frequent across much of the Southwest Power Pool (SPP). Another cluster of negative prices can be found in the Permian basin in western Texas, a region with not only many oil and gas wells, but also wind turbines and, increasingly, solar plants, but with limited transmission capacity. These two negative price clusters illustrate two different drivers of negative prices, geographically isolated hotspots driven by transmission constraints (e.g., the Permian basin), and region-wide negative prices driven by the high penetration of wind power (e.g., SPP) (Seel et al. 2021).

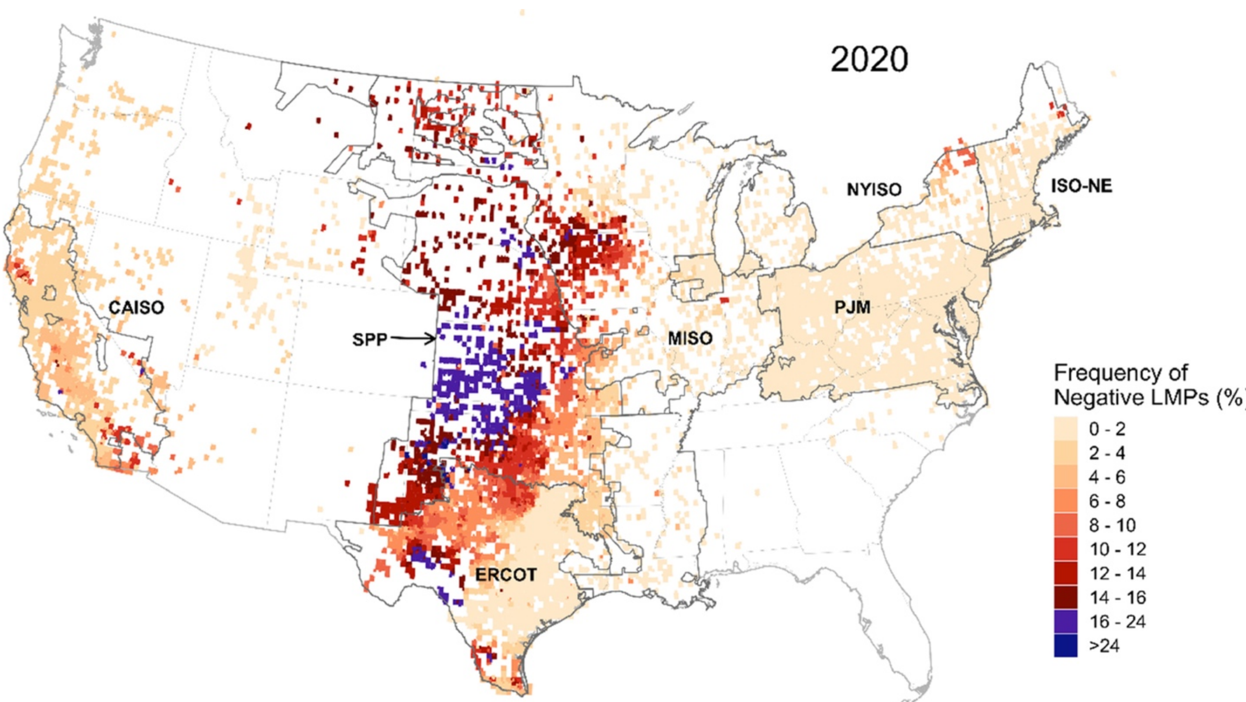

Figure 6. Frequency of Negative LMPs at Nodes in the Seven Organized Wholesale Markets in the United States. Source: Seel et al. 2021.

In addition to the locational features of negative locational marginal pricing (LMP) in the United States in 2020, Figure 7 shows the average prices and the frequency of negative prices at all LMPs from 2006 through 2020. The continued increase of negative price frequency and the decline of wholesale prices was not exceptional in 2020 compared to the historical trends, even though COVID demand shocks may have exacerbated both (Seel et al. 2021).

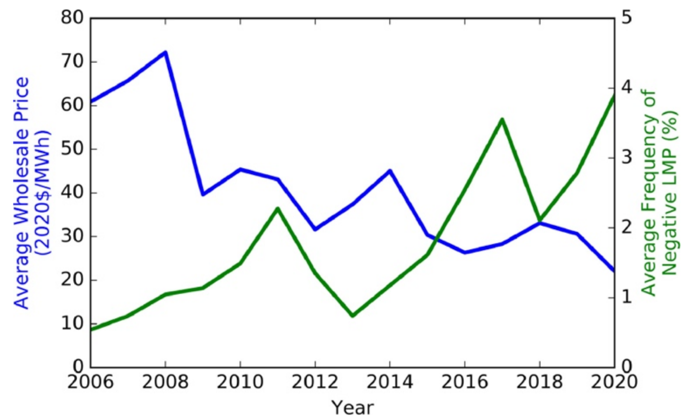

Figure 7. Average Wholesale Prices and Average Frequency of Negative LMP at Nodes in the Seven Organized Wholesale Markets in the U.S. Source: Seel et al. 2021.

In addition to the increasing frequency of negative price spikes, some markets are also experiencing an increasing frequency of positive price spikes, though the relation of these price spikes to increasing penetration of VREs is ambiguous. Figure 8 shows the frequency of price spikes above $250/MWh in major electricity market hubs. There is some indication of an increasing trend in price spikes in the major hubs of SPP, Midcontinent Independent System Operator (MISO), PJM, NYISO, and ISO-NE; however, while CAISO and Electric Reliability Council of Texas (ERCOT) have a larger share of price spikes than other markets, there is no obvious correlation between increases or decreases in price spikes with increasing penetration of VREs.

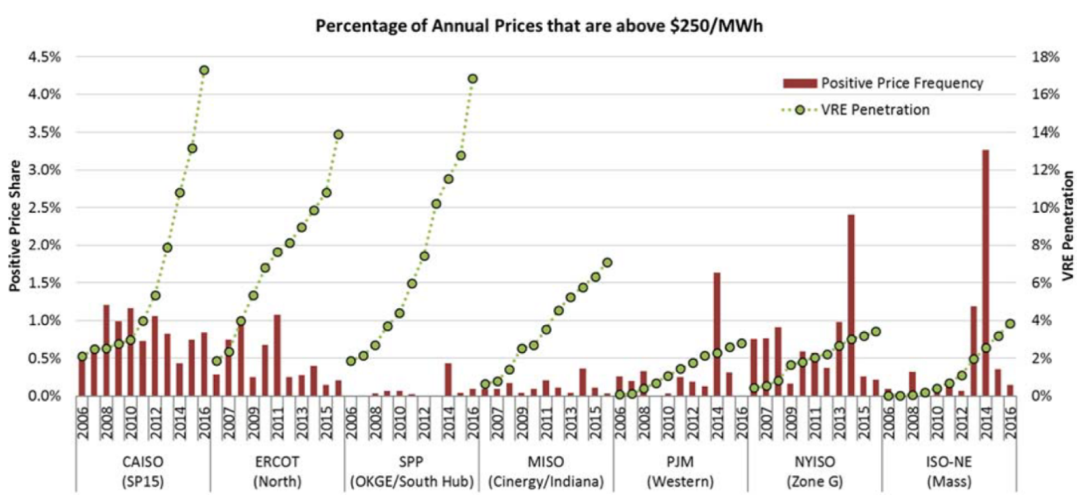

Figure 8. Positive Price Spike (>$250/mwh) Shares. Source: Wiser et al. (2017).

Increases in positive and negative prices point to VREs also potentially affecting price volatility, though the literature on the direction of the impact (an increase or decrease in volatility) is inconclusive. Woo et al. (2011), Astaneh et al. (2013), Clò et al. (2015), Seel et al. (2018), Johnson and Oliver (2019), and Mwampashi et al. (2020), among others, found VREs increase volatility, whereas Rintamaki et al. (2017) and Pereira da Silva and Horta (2019), among others, found evidence of the opposite effect, as will be discussed in more detail in Section 2.2.1 and Section 2.2.2). Adjusting power supply to address forecasting errors from VREs can lead to periods of high or negative prices, which affects the energy sales for all other resources, as well as increases investor risk. The volatility of electricity prices, measured as its standard deviation, is shown in Figure 9. There is some evidence of an increasing trend in price volatilities in most of the hubs. However, the causal relationship between VRE penetration and the trends in price volatilities needs further investigation, as there are many other major factors, such as weather events, causing the price spikes.

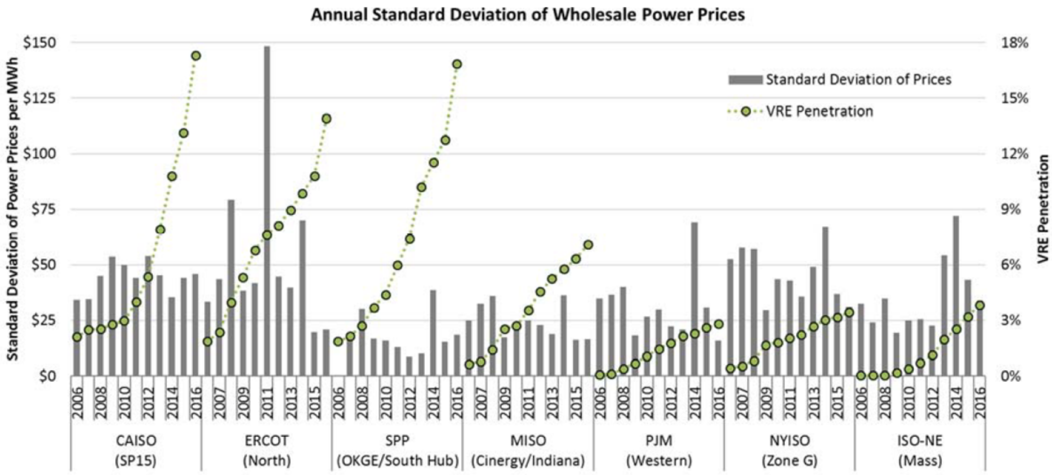

Figure 9. Annual Standard Deviation of Electricity Prices. Source: Wiser et al. 2017.

Although federal- and state-level subsidies for producing clean energy can allow zero marginal cost resources to earn revenue from policy subsidies even when energy prices are negative, in some cases, VRE plants are forced to curtail their output due to two main reasons: system-wide oversupply and local transmission constraints. Curtailment due to system-wide oversupply occurs when, on a large scale, there is simply not enough demand for all the renewable electricity that is available. As shown in Figure 10, which shows the monthly wind and solar curtailments in CAISO, curtailments happen most frequently in spring months. Curtailments due to local transmission constraints occur when there is so much renewable electricity in a local area that there is insufficient transmission infrastructure to deliver that electricity to a place where it could be used. Handleeman (2015) shows that the wind energy curtailment fell from 17% to 0.5% in 2014 mostly due to construction of additional transmission lines to move that wind energy out of local pockets to places where it could be used. Disentangling the effect of VREs from policy incentives and curtailments on electricity prices is another challenge to uncover the true contribution of VREs.

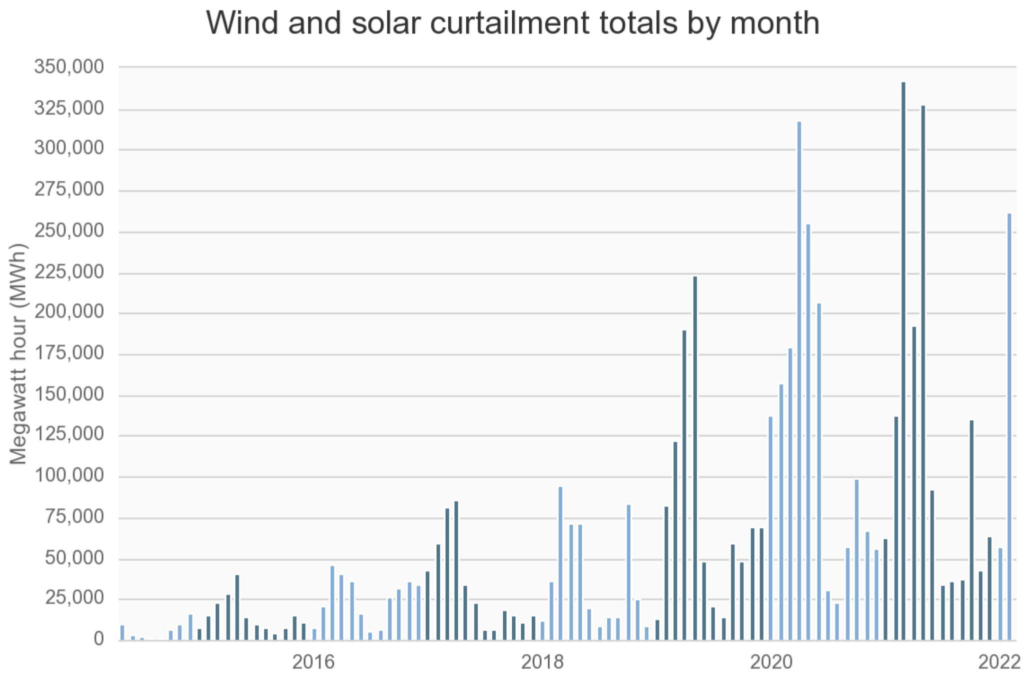

Figure 10. CAISO Wind and Solar Monthly Curtailment. Source: CAISO.

To summarize existing trends affecting price formation processes, zero marginal cost resources not only displace more expensive resources, but through their contribution to low wholesale electricity prices, and even negative electricity prices, also reduce energy sales from other resources. Further, they can potentially increase price volatility, which increases price risk for all market participants and investors. While low prices are great for consumers—if they are realized in the retail prices—these issues can lead to revenue sufficiency problems for power producers.[1]

2.1.1 Price Formation and Reliability – Background and Relevant Trends

In wholesale electricity markets, energy prices are largely determined by the intersection of electricity supply—as determined by the dispatch curve—and demand. However, some unique characteristics of electricity introduce challenges—many consumers are not price-sensitive due to a lack of real-time metering and billing, making demand very inelastic, and there is a lack of large-scale economical storage. Because grid operators must ensure that supply meets demand every second of the day, situations can arise where electricity supply is not sufficient to meet inelastic consumer demand, resulting in a supply shortage. For these reasons, regulatory policies to ensure reliability (i.e., ensuring sufficient power plants are available to safely produce the power demanded by consumers) are currently necessary. Further, reliability is intricately linked to price formation and revenue sufficiency as power plants need to collect most of their

[1] As an example of how retail prices are affected by factors other than the cost of generation, Borenstein et al. (2021) point out that, despite increasing amounts of zero marginal cost renewable resources, the average price of residential electricity in California is 45 – 80% higher than the national average, they attribute this cost to the high fixed costs levied through volumetric charges. The fixed charges are driven by past purchases of renewable electricity at above-market costs, fixed costs of transmission and distribution (including wildfire-related charges), and energy efficiency and other public program expenditures. The fixed charges are double to triple the marginal cost of producing electricity.

revenues during these periods of supply shortages, which may be difficult if administratively set shortage or scarcity prices are too low (Zhou et al. 2021).

To administratively set shortage pricing, markets typically use value-of-lost-load (VOLL) pricing, which sets the price equal to customers' willingness-to-pay to avoid losing power (the duration that the shortage price will last is also set administratively) (Stoft 2002). In the United States, this is typically accomplished by requiring operating reserves for a fixed percentage of demand.[1] When operating reserves fall below the required level, shortage pricing is used to bring more resources online.

However, operating reserve pricing can be divorced from energy market outcomes if there is not a reliability component including in the pricing mechanism (Cramton et al. 2013). For example, PJM previously had two types of operating reserves: Tier I for online units that had available capacity and could respond voluntarily to events within 10 minutes, and Tier 2 reserves for resources that cleared the Synchronized Reserve Market and were obligated to respond to declared events (PJM 2018). Tier 2 resources operated at a lower point than their economic dispatch and were compensated according to their opportunity costs, but subject to a penalty if they did not respond to an event. Tier 1 resources, on the other hand, were procured through the energy market, paid for their services if they responded, but not subject to a penalty if they did not. Further, pricing in PJM for operating reserves was based on penalty factors (up to $850/MWh in 2019) when reserves fell below required levels, which was far less than the VOLL. This difference in pricing and participation requirements lead to reliability issues as Tier 1 resources only responded to reliability events 60.1% of the time, whereas Tier 2 resources responded 87.6% of the time (Hogan and Pope 2019).

Linking operating reserve pricing with energy market outcomes becomes even more important with increasing penetration of VREs, as better scarcity pricing can incentivize supply and responsive load to respond where and when it is needed (Hogan and Pope 2019). This can be achieved through communicating the value of additional capacity during scarcity situations through the energy and reserve prices paid to all resources and all loads to incentivize price-response.

Some recent developments have aimed to improve shortage pricing mechanisms, such as the operating reserve demand curve (ORDC) in ERCOT and PJM, to better align price incentives to reflect the value of operating reserves under different operating conditions and geographic locations (Hogan and Pope 2019). The value, or shortage price, of the ORDC is the loss of load probability (LOLP)[2] at a particular reserve level, multiplied by the VOLL. For example, in PJM's ORDC design, maximum reserve clearing prices were supposed to increase up to $14,000/MWh when the ORDC was fully implemented in May 2022, to better align the value of reserves with operating requirements (PJM 2021a).[3] However, elements of the ORDC design in PJM are still being determined after a series of recent decisions from the Federal Energy

[1] For example, for WECC the NERC standard is the greater of either 1) the loss of the most severe single contingency, or 2) the sum of 3% of hourly integrated load plus 3% of hourly integrated generation (WECC 2021).
[2] The LOLP is based on the mean and standard deviation of the error from forecasted system reserves compared to reserves available in real time. LOLP is the probability of a loss of load event compared to a risk-based cutoff value for each reserve level. See Hogan and Pope (2019) for further details.
[3] PJM clarifies that $ 12,000/MWh is the sum of energy price cap of $2,000/MWh plus the stacking of five $2,000/MWh Reserve Penalty Factors, noting that the $12,000/MWh figure could rise to $14,000/MWh if PJM models a subzone for the 30-minute requirement (Monitoring Analytics 2021).

Regulatory Commission (FERC), reversing approval of some elements PJM's ORDC redesign, and penalty factors currently remain at $850/MWh.[1]

Other markets, such as NYISO, ISO-NE, and MISO, have also implemented alternative pricing for fast start units or extended locational marginal price formation, which allows for no-load or start-up costs to be included in resources' supply bid, helping to cover the true cost of operating that resource (Sun et al. 2021). While these pricing mechanisms aim to better align resource value with operating requirements, they do not eliminate the uncertainty and risk from scarcity events. Infrequent scarcity events that result in high price spikes increase uncertainty and price risk, discouraging investment, whereas regulatory policies that encourage low and long duration price spikes reduce uncertainty and price risk (Stoft 2002). Uncertainty and risk affect both investors and customers, as experienced in Texas' extreme winter weather event in February 2021:

> *The Public Utilities Commission of Texas (PUCT) implemented an ORDC Curve in 2014 to improve scarcity pricing. The value of the ORDC "price adder" curve at any given level of operating reserves is determined by the LOLP at that reserve level, multiplied by the VOLL. The VOLL, or high-system-wide-offer cap (HCAP), was capped at $9,000/MWh. In February 2021, an extreme winter weather event led to severe energy infrastructure failure and blackouts, leaving 4.5 million homes without power for several days, causing loss of life. Although the power system failure did not have one single cause, risk to both market participants and consumers of the current ORDC design was judged to be too great. Following the event, the PUCT lowered the HCAP to $5,000/MWh and redesigned the ORDC to provide a lower but longer duration price spike (ERCOT 2014; PUCT 2021; King et al. 2021).*

While the PUCT changed the parameters of the ORDC to reduce risk to market participants, to ensure adequate capacity is available, most markets use some form of capacity procurement mechanism. Two dominant forms are capacity payments and capacity markets.[2] Capacity payments are used to pay power producers regular amounts to cover their capital costs, addressing the missing money problem (from power producers missing out on scarcity revenues due to price caps or low average energy prices) and properly signaling investment. Capacity markets, on the other hand, set a resource adequacy target and then determine the amount of capacity needed to achieve the target (Kirschen and Strbac 2018). Compared to the ORDC approach, capacity mechanisms provide a lower payment on a $/MWh basis (PJM's 2022/2023 Base Residual Auction (BRA) cleared at $50/MW-day, equivalent to $2.08 $/MWh) but the payment is provided with regularity. However, due to the intermittent nature of VREs, higher reliability targets may be needed as wind and solar become a larger part of the generation portfolio, leading to excess capacity (Frew et al. 2016). For example, PJM found that serving 50% renewable penetration required "…an additional 78% nameplate capacity on top of the forecasted peak load … to satisfy the 1-in-10-year loss of load expectation (LOLE)" (PJM 2021b). Excess capacity in systems with high amounts of renewable energy means that these systems could be expensive.

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[1] See *PJM Interconnection, L.L.C.*, 171 FERC ¶ 61,153 (May 2020 Order); *PJM Interconnection, L.L.C.*, 177 FERC ¶ 61,209 (2021) (Remand Order); *PJM Interconnection, L.L.C.* 180 FERC ¶ 61,051 (2022) (July 2022 Order)

[2] PJM, ISO-NE, MISO, and NYISO have centralized capacity markets. CAISO and SPP have resource adequacy requirements for load-serving entities. ERCOT has an energy-only market with high price caps and the ORDC price adder to reflect the value of operating reserves (Byers et al. 2018).

As a case in point, CAISO's duck curve, shown in Figure 11, demonstrates the reliability challenges from increasing amounts of VREs. The duck curve is CAISO's net demand (demand or forecasted demand less actual or forecasted renewables production). What it shows is the shape of demand that CAISO must meet with dispatchable resources—typically, natural gas and hydropower plants. In the daylight hours—because California has a lot of solar capacity—the belly of the duck forms, and this is when CAISO is at risk of overgeneration, or electricity supply exceeding demand. When solar power production tapers off for the day, the neck of the duck forms, creating a ramp that needs to be met with flexible resources that can produce a lot of power in a short amount of time.

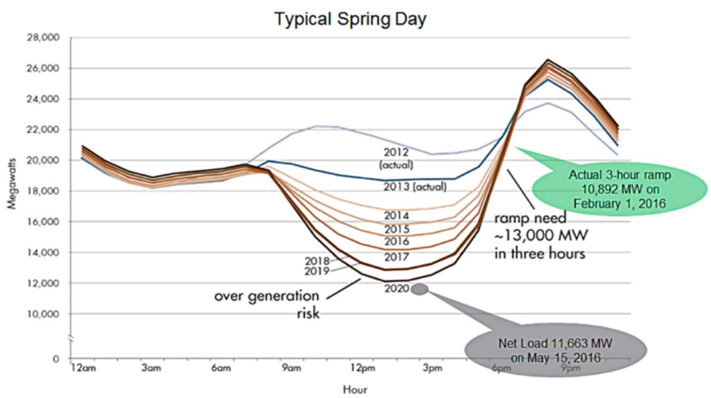

Figure 11. California's Duck Curve. Source: CAISO.

These operating conditions—including short, steep ramps, potential for overgeneration, as well as decreased frequency response—drive changes in electricity grid operations (CAISO 2016). These operational challenges require flexible resources to respond to short and steep ramps as well as react quickly to changing grid conditions. Frequent stops and starts make ensuring reliability expensive and emissions intensive for flexible fossil-fuel-fired generators (Lew et al. 2013; Bloom et al. 2016). Additionally, periods of oversupply (overgeneration) can create very low, or even negative, wholesale prices, compounding revenue sufficiency challenges. To address these and other challenges, CAISO has created the Western Energy Imbalance Market (EIM) to make surplus renewable energy available to a larger geographic area (as well as have access to a larger pool of flexible resources), improving renewables integration (CAISO 2018). In addition, California has promoted increasing amounts of energy storage with its energy storage mandate.

The impact of VREs on reliability are addressed in a few ways. The first is through understanding the impacts of VREs on price formation processes (including energy, flexibility, and capacity prices) that influence reliability, discussed in the next section. The second is through understanding the impact on revenue sufficiency, as discussed in Section 3.0. The third is through changes in market design, such as the EIM, discussed in Section 5.0.

2.2 Empirical Evaluation of VRE Impacts on Price Formation

Market trends indicate that increasing amounts of VREs could impact price formation processes, but price formation challenges in electricity markets today are not solely due to VREs. Declining natural gas prices; changing resource mixes; different electricity market designs and mechanisms to manage energy, ancillary service, and capacity markets; and regulatory policies all factor into the challenges faced by electricity market operators and participants today. Parsing out these varied drivers of electricity market challenges is necessary to understand the true impact of VREs. Understanding this impact on average, over time, and by geographic location will help to determine how future market and grid processes need to change to better accommodate resource mixes with high levels of VREs.

In the related literature, there are typically two approaches to evaluate the impact of increasing amounts of VREs on wholesale market prices and other electricity market outcomes: ex ante simulations and ex-post empirical analyses (e.g., ex ante simulations could be used to model potential future impacts of VREs on energy prices, based on a set of assumptions, whereas ex-post empirical analyses examine actual outcomes of VREs on energy prices, using market data). Simulations can be used to model electricity markets, but they tend to be non-transparent and resource intensive (Callaway and Fowlie 2009) as well as sensitive to underlying assumptions (Cullen 2013). Ex-post empirical analyses (regression analyses) can simplify estimation strategies as they are more transparent and less resource intensive as they use publicly available data and standard statistical packages, but they are conditional on the quality of the underlying data (Callaway and Fowlie 2009). Further, ex-post empirical analyses are typically limited to estimating short-term merit-order effects (Cludius et al. 2014), although the more recent literature has provided some ways forward in estimating long-term effects from historical data by focusing on estimating the impacts of increasing levels of VRE capacity over time on long-term energy prices (Bushnell and Novan 2018). As will be discussed in this literature review, a substantial amount of research has been devoted to determining the actual impact of VREs on short-term energy prices. However, VRE price impacts on ancillary service, capacity, and PPA markets are less well known.

2.2.1 Short-Term Energy Price Impacts

Through ordinary least squares (OLS), time series, or panel data regressions,[1] most of the related literature finds that increasing amounts of VREs cause short-term energy prices to decline.[2] As current electricity prices are likely correlated with past values, many studies use autoregressive model structures (which include a lagged price variable to account for time dependency between prices), first-differences, or logged price data[3] and adjust standard errors for autocorrelation using a number of techniques, including Newey-West standard errors, Driscoll-Kraay standard errors, cluster robust standard errors, or other feasible generalized least squares estimators, such as the Prais-Winston estimator, depending on the data and autocorrelation structure.[4] By controlling for exogenous energy price determinants from supply

[1] They key difference with time series regressions is that they focus on a single unit at multiple time intervals, whereas panel data regressions focus on multiple units at multiple time intervals, where a unit may be ISO-level or intra-ISO-level locational marginal prices.

[2] For a survey of other approaches in the literature, see Cludius et al. 2014.

[3] These data transformations are done to make the time series stationary as a non-stationary time series could lead to spurious results. Stationarity in the data can be tested with a unit root test such as the Augmented Dickey-Fuller test. Lags of variables are also included to address the time-dependent nature of price variables.

[4] Autocorrelation occurs when error terms are correlated over time, violating a basic assumption of the ordinary least squares model, creating bias. Autocorrelation is dealt with by adjusting standard errors to be robust to autocorrelation and heteroskedasticity (for example, with Newey-West standard errors for time series data or Driscoll-Kraay or cluster robust standard errors for panel data), or by transforming the data and using generalized least squares (GLS) or using feasible generalized least squares (FGLS) to model the autocorrelation. With GLS or FGLS, the econometrician must know enough about the autocorrelation process in the data to model it specifically, which allows for a more efficient estimator and smaller standard errors.

and demand factors as well as for observed and unobserved energy price determinants through a set of fixed effects,[1] common findings are that price effects vary temporally and geographically, by market size and market conditions, as well as by the underlying resource portfolio, as the marginal generator displaced by the VRE has a significant impact on price effects. Owolabi et al. (2021) point out that because of the inherent distributional changes of electricity prices due to VREs, more robust modeling methods may be needed.[2]

2.2.1.1 Literature Review on Short-Term Energy Price Impacts

Early literature on price impacts in U.S. markets tend to focus on a single market using time series regressions to predict[3] the impact of increasing levels of wind or solar generation on energy prices (and volatility, in limited studies) based on observed historical data.[4] Woo et al. (2011) found that increasing amounts of wind generation (from 500 MW to over 7,500 MW from 2007 to 2010) led to declines in 15-minute balancing market prices in the ERCOT market. Price declines ranged from $3.2/MWh to $15.3/MWh for 1 gigawatt hour (GWh) of wind production,[5] depending on the market zone (and its transmission constraints), with the greatest price declines occurring in the West, where the wind energy resources were located but there was limited transmission for exporting power to other zones.[6] The findings echoed those of Nicholson et al. (2010), where a 1 GWh increase of wind generation in Texas caused 15-minute balancing market prices to decrease from $0.67–$16.4/MWh depending on the ERCOT zone, with the largest decrease again occurring in the Western zone. But estimates of energy price declines due to VREs also depend on the underlying resource mix. In Texas, the marginal generator displaced by a wind resource is a natural gas generator, which can result in significant price declines. Woo et al. (2013) examined the hydropower-rich Pacific Northwest for price declines from wind resources. They found that there were small but statistically significant wholesale price declines from $0.72–0.96 /MWh for 1 GWh of wind generation due to readily available hydropower capacity and limited transmission constraints in the region. Although the costs of integrating wind into the hydro-rich system were lower, so were benefits from investing in wind power, as prices were not reduced as much as in markets dominated by thermal generation.

Woo et al. (2016) explored the merit-order effects of both solar and wind energy as well as how much prices diverge from day-ahead to real-time markets due to forecast errors in renewable energy production in California from 2012 to 2015. They found that a 1 GWh increase in solar

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[1] Fixed effects are commonly used in econometric analyses of data with a time or cohort dimension to control for unobserved but fixed omitted variables (Angrist and Pischke 2009)

[2] Owolabi et al. (2021) highlight that this is especially true for simulation approaches, which tend to assume a linear relationship between electricity prices and VREs with a constant variance.

[3] Although the models used in the early literature are primarily autoregressive models that use historical observations to predict future LMP values, these models also incorporate a variety of controls to parse out the effect of increasing wind generation. As such, results are included in this review.

[4] The literature uses the wind or solar generation data to estimate the impact of renewables on electricity prices. The price impacts are estimated for hourly, 15 minute, or daily average price data. The specific price data and time periods are detailed in Table 1, Table 2, and Table 3.

[5] Price effects have been converted to show the effect per 1 GWh of wind or solar production for comparability purposes.

[6] Woo et al. (2011) estimated price effects at the zonal level, noting (in Woo et al. 2013) that ERCOT's Houston, North, and South zones have little wind generation and interzonal transmission congestion, whereas ERCOT's West zone has most of the wind generation capacity and limited transmission for exporting wind power to other zones. Transmission constraints (or curtailment) were not explicitly controlled for in the analysis.

energy reduced day-ahead market prices by \$1.0–\$5.3/MWh, depending on the location of solar resource. They found a similarly sized increase in wind generation decreased day-ahead market prices by \$1.4–\$3.4/MWh. Real-time market price effects were slightly lower for solar (\$1.0–\$3.7/MWh decrease for a 1 GWh increase), and slightly higher for wind (\$1.5–\$11.4/MWh decrease for a 1 GWh increase) compared to day-ahead market prices, a difference attributed to forecast errors. However, energy price impacts from natural gas prices were much more substantial than the merit-order effect from wind and solar—a \$1/MMBtu increase in natural gas prices raised day-ahead market prices by \$7.5/MWh and real-time market prices by up to \$8.7/MWh. Using a simulation approach, Wiser et al. (2017) found similar results to Woo et al. (2016); natural gas price declines explained 85–90% of wholesale market price declines. These results point to the importance of parsing out price effects due to renewable energy from other factors, especially natural gas prices. More recent literature in the United States has focused on determining the causal effect of wind or solar resources on energy prices by using linear or nonlinear regression methods and adjusting standard errors to be robust to autocorrelation and heteroskedasticity. Further, panel data methods are also used by combining data from multiple ISOs/RTOs, as in Owolabi et al. (2021), or by using more granular (nodal) data, as in Tsai and Eryilmaz (2018). In this literature, VREs are found to consistently decrease short-term energy prices, although magnitudes tend to be smaller than those found in the early literature. Additionally, Owolabi et al. (2021) found that the price-reducing effect of increased VRE penetration is nonlinear, with the greatest impact observed in the reductions of extremely high system electricity prices. However, correlation between negative electricity prices and VRE penetration was inconclusive across the seven ISOs in their study (ISO-NE, NYISO, PJM, MISO, SPP, ERCOT and CAISO).

Outside of the United States, research from Europe and Australia has found similar conclusions—that increasing levels of VREs cause wholesale price declines, but the decline depends on the type of resource (wind or solar), the regional resource mix (and what type of power producer is on the margin), and the window of time for which the energy price effect is analyzed (on average, by season, or by hour of day). Different from predominant approaches in the U.S. literature, several studies have also focused on merit-order effects over time, finding that VREs cause short-term energy prices to decrease, but with a diminishing magnitude over time.

Gelabert et al. (2011) analyzed wholesale price effects from renewables and energy-efficient cogeneration in Spain from 2005 to 2010 and found a 2€ reduction in wholesale prices for a 1 GWh increase in renewables and cogeneration technologies. With a similar approach, Cló et al. (2015) found that an increase of 1 GWh of wind and solar in Italy reduced electricity prices by 2.3€/MWh and 4.2€/MWh, respectively, from 2005–2013. O'Mahoney and Denney (2011) examined the impact of increased levels of wind generation on wholesale prices in Ireland in 2009, finding the wholesale price significantly decreased by nearly 10€/MWh due to increased wind generation, likely due to the share of wind generation relative to the market size in Ireland. Further, O'Mahoney and Denney (2011) considered the effects of wind over time on prices and found that wholesale price declines increased significantly in the evening hours, when wind was a larger share of the generation mix.

Würzburg et al. (2013) quantified renewable energy's impact on wholesale prices in Germany and Austria from 2010 to 2012. Using a range of assessment methods, they found an increase of 1 GWh of renewable energy caused price declines of roughly 1€/MWh; further, wind and solar had roughly equivalent price impacts. In a more recent analysis, Cludius et al. (2014) found even larger price effects for the German market, with wind and solar photovoltaic (PV) reducing market prices in Germany by 6€/MWh in 2010, rising to 10€/MWh in 2012. Gürtler and

Paulsen (2018) found negative, but smaller effects of wind and solar on German electricity prices, with 1 GWh of wind or solar decreasing prices by 0.6€/MWh from 2010 to 2016; they concluded that declining fuel prices reduced the price-dampening effect of wind and solar since 2013. Maciejowska (2020) also found that increasing levels of wind and solar had roughly equivalent impacts on the price level in the German market from 2015 to 2018; however, when considering the distribution of prices, wind generation tended to reduce prices more than solar during low price periods, whereas solar tended to reduce prices more during high price periods. Jónnson et al. (2010) found the opposite effect when examining the impact of VREs on the distribution of prices in Denmark from 2006–2007; wind power's greatest reduction of energy prices occurred during high demand periods.

In more recent European literature, Hirth (2018) used an ex-post factor decomposition analysis to explain the determinants of electricity price declines in Germany and Sweden, which dropped by nearly two-thirds from 2008 through 2015. Although this paper used a simulation approach, it was performed on ex-post data and had similar outcomes to the real world. Hirth (2018) found that—although the two markets studies were markedly different—the expansion of renewable energy was the single largest factor depressing prices in both markets. In Germany, renewable energy was responsible for 24% of the price decline and in Sweden, 35%.

Researchers have also investigated the merit-order effect over time, including Gelabert et al. (2011), Cludius et al. (2014), Cló et al. (2015), and Gürtler and Paulsen (2018). Table 2 provides a summary of the marginal price effects over time from these papers. These studies focus on the European countries and have found somewhat consistent results. The estimated magnitude of the marginal effect of VREs on short-term energy price, in general, decreases over time.

Table 2. Marginal Price Impacts from VREs Over Time

Paper	Method	Country	VRE-Type	Period	Price Impact (Price decrease per additional 1GWh of VRE)	Price Data
Gelabert et al. (2011)	Multivariate regression model (OLS regression with first-differenced data and Newey-West standard errors)	Spain	Renewables	2005-2010	2 €/MWh	Daily average of hourly prices
				2005	3.8 €/MWh	
				2006	3.4 €/MWh	
				2007	1.7 €/MWh	
				2008	1.5 €/MWh	
				2009	1.1 €/MWh	
				2010	1.7 €/MWh	
Cludius et al. (2014)	OLS regression on time series data with Newey-West standard errors	Germany	Wind	2008	2.27 €/MWh	Day-ahead hourly prices
				2009	1.72 €/MWh	
				2010 (2nd half)	1.15 €/MWh	
				2011	0.97 €/MWh	
				2012	0.97 €/MWh	
				2010-2012	1.07 €/MWh	

Paper	Method	Country	VRE-Type	Period	Price Impact (Price decrease per additional 1GWh of VRE)	Price Data
			Solar	2010 (2nd half)	0.84 €/MWh	
				2011	0.90 €/MWh	
				2012	1.37 €/MWh	
				2010-2012	1.14 €/MWh	
Cló et al. (2015)	Generalized least squares regression with the Prais-Winston estimator to model serially correlated, first-order autoregressive errors	Italy	Solar	2005-2013	2.3 €/MWh	Daily average of hourly prices from day-ahead market
				2011	4.64 €/MWh	
				2012	3.47 €/MWh	
				2013	3.45 €/MWh	
			Wind	2005-2013	4.2 €/MWh	
				2008	9.59 €/MWh	
				2009	7.25 €/MWh	
				2010	5.07 €/MWh	
				2011	5.77 €/MWh	
				2012	4.38 €/MWh	
				2013	2.86 €/MWh	
Gürtler and Paulsen (2018)	Fixed effect regression with hourly fixed effects and Driscoll-Kraay standard errors	Germany and Austria	Wind	2010	1.2 €/MWh	Day-ahead and intraday hourly prices
				2011	1.2 €/MWh	
				2012	1 €/MWh	
				2013	1.2 €/MWh	
				2014	1 €/MWh	
				2015	0.8 €/MWh	
				2016	0.6 €/MWh	
			Solar	2010	0.3 €/MWh	
				2011	0.8 €/MWh	
				2012	0.9 €/MWh	
				2013	1.1 €/MWh	
				2014	1.0 €/MWh	
				2015	0.9 €/MWh	
				2016	0.6 €/MWh	

Table 3 provides a comprehensive summary of the different empirical approaches and some commonly cited simulations that have quantified the effects of renewable production on short-term electricity prices in different regions in the United States, and Table 4 provides a similar summary for other countries. The studies that have investigated the impact of renewable generation on electricity price volatilities are also summarized in Section 2.2.2.1.

Table 3. Literature on Short-Term Price Effects of Renewable Generation in the USA

Paper	Methodology	Region	VRE-Type	Period	Reported Price Change[1]	Impact on Price Volatility[2]	Price Data Utilized
Nicholson et al. (2010)	ARMAX (see Section A.1.2 for a detailed description of this model)	ERCOT	Wind	2007–2009	$0.67-$16.4 /MWh		Hourly zonal balancing-energy market prices
Woo et al. (2011)	Autoregressive model: linear AR(1) partial adjustment model estimated by maximum likelihood estimation. The adjustment is from the lagged price variable[3]	ERCOT	Wind	2007-2010	$3.2-$15.3 /MWh	Volatility is defined as variances of spot prices. Wind generation enlarges the price volatility	15-min zonal balancing-energy market prices

[1] This column provides the reported price decrease due to additional 1 GWh of corresponding renewable resources.
[2] This column provides a summary of the measurement and modeling of price volatilities and the impact of renewables on price volatilities in the paper, if it has been investigated in the paper.
[3] Note that autoregressive models as described above are typically used for forecasting rather than causal analysis. With this paper, the intent was to enable a direct prediction of the effect of an increase in wind generation on spot prices and variance.

Paper	Methodology	Region	VRE-Type	Period	Reported Price Change[1]	Impact on Price Volatility[2]	Price Data Utilized
Woo et al. (2013)	Autoregressive model: linear autoregressive (AR(1)) partial adjustment model estimated by maximum likelihood estimation. The adjustment is from the lagged price variable	Pacific Northwest	Wind	2007-2012	$0.72-0.96 /MWh		Day-ahead daily prices averaged from hourly data
Woo et al. (2016)	Seemingly unrelated regression to estimate a system of four price regressions with errors assumed to follow a stationary AR (4) process	CAISO	Solar	2012-2015	$ 1.0-$5.3 /MWh		Day-ahead hourly
					$1.0-$3.7 /MWh		Real-time hourly
			Wind		$1.4-$3.4 /MWh		Day-ahead hourly
					$1.5 - $11.4 /MWh		Real-time hourly
Wiser et al. (2016)	Simulation (AVERT Tool)	Various regions	Renewable generation used to meet 2013 renewable portfolio standard (RPS) compliance	2013	$0 to $ 4.6/MWh		Simulated hourly wholesale prices
Zarnikau et al. (2016)	Seemingly unrelated regression to estimate a system of eight price regressions with errors assumed to follow a stationary AR (n) process	ERCOT	Wind	2011-May 2015	$0.043 - $ 6.08 /MWh (forecasted wind generation on Day-Ahead Market [DAM])		Hourly DAM and real-time market (RTM) prices. (Zonal prices are load-weighted average prices of intrazonal nodes)
					$1.42 - $7.2 /MWh (actual wind generation on RTM)		
Wiser et al. (2017)	Simulation	ERCOT	Wind	2008-2016	$0.7 /MWh		Simulated hourly wholesale prices
			Solar	2008-2016	$0/MWh		
		CAISO	Wind	2008-2016	$0.4/ MWh		
			Solar	2008-2016	$1.9/ MWh		
Jenkins (2017)	Time series linear regression with time fixed effects	PJM	Wind	2008-2016	$1 -$2.5/MWh		Daily average LMP (average over hourly data, prices are logged)

Paper	Methodology	Region	VRE-Type	Period	Reported Price Change[1]	Impact on Price Volatility[2]	Price Data Utilized
Haratyk (2017)	Simulation	Midwest	Wind	2008-2015	$4.6 / MWh		Simulated hourly prices
		Mid-Atlantic	Wind	2008-2015	$ 0/MWh		
Tsai and Eryilmaz (2018)	Fixed effect regression with month by year and date fixed effects and cluster robust standard errors	ERCOT	Wind	2014-2016	$1.45-$4.45 /MWh		15-minute nodal real-time prices
Craig et al. (2018)	OLS regression on time series data with Newey-West standard errors and block bootstrapped standard errors	CAISO	DG Solar	2013-2015	$2.7–3.1/MWh		Day-ahead average hourly prices
Zarnikau et al. (2019)	Seemingly unrelated regression to estimate a system of six energy price and ancillary service price regressions with errors assumed to follow a stationary AR(3) process	ERCOT	Wind	2011-2017	$1.64 /MWh (1 GWh increase of Wind Forecast on DA hourly prices)		Day-ahead hourly prices
					$2.3/MWh (1 GWh increase in wind generation forecast error on RTM hourly		Real-time hourly prices

Paper	Methodology	Region	VRE-Type	Period	Reported Price Change[1]	Impact on Price Volatility[2]	Price Data Utilized
Quint and Dahlke (2019)	Four different econometric models: (1) Cross-sectional multivariate regression (assumes intertemporal independence of prices) (2) Prais-Winsten model to allow for autocorrelated and autoregressive prices (3) Seasonal Autoregressive Moving Average with Exogenous Regressors (SARMAX) Model (see Section A.1), and (4) Cross-sectional multivariate model with quadratic terms to allow for non-linearity in exogenous supply and demand control variables	MISO	Wind	2008-2016	$1.4 - $ 3.4 /MWh		Real-time hourly prices
Mills et al. (2021)	Simulation	Various Regions	Wind and Solar	2008-2017	< $ 1.3 /MWh (other regions) $2.2/ MWh (CAISO)		Real-time hourly prices
Owolabi et al. (2021)	Quantile regression and skew t-distribution regression	Various Regions	Wind and Solar	2014-2020	$0.37 - $ 6.96 /MWh detrended system prices		Real-time hourly prices

Table 4. Literature on Short-Term Price Effects of Renewable Generation in Other Countries

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
O'Mahoney and Denney (2011)	Time series OLS regression with robust standard errors	Ireland	Wind	2009	10 €/MWh		Real-time hourly prices
Würzburg et al. (2013)	Multivariate regression model (OLS regression with first-differenced data and Newey-West standard errors)	Germany and Austria	Wind and Solar	2010-2012	1 €/MWh		Day-ahead daily price averaged from hourly prices
Forrest and MacGill (2013)	Autoregressive model: linear AR(1) partial adjustment model estimated by both OLS with Newey-West standard errors and a Tobit model due to truncated price data. The adjustment is from the lagged price variable	Australia	Wind	2009-2011	8.05 AUD /MWh for SA (South Australia) 2.73 AUD/MWh for VIC (Victorian)		30-minute prices averaged from five-minute prices. Data was truncated between an upper bound of $415/MWh and a lower bound of $1/MWh.
Keles et al. (2013)	Combined model of simulation of energy prices and wind feed in and an autoregressive linear regression to determine price-reducing effect of wind	Germany	Wind	2006-2009	Average prices reduced by 5.90€/MWh for an average wind power factor of about 4670 MW.		Day-ahead hourly prices are simulated

[1] This column provides the reported price decrease due to additional 1 GWh of corresponding renewable resources.

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
Ketterer (2014)	Generalized autoregressive conditional heteroskedasticity (GARCH) model with number of autoregressive lags which minimize the Bayesian information criterion (see Section 8.0A.1.5A.1.5) and a 3-year rolling window	Germany	Wind	Jan 2006-Jan 2012	When the share of wind rises by one percentage point, the electricity price decreases by 1.46%	Price volatility is modeled using the variance equation in the GARCH system. Variable wind power increases price volatility	Daily data averaged from hourly day-ahead data. Extreme outliers are replaced with the value of three times the standard deviation for the respective weekday
Paraschiv et al. (2014)	State space model (time-varying regression model with lagged electricity prices included to reduce autocorrelation in the data). The model is estimated with the Kalman Filter and maximum likelihood.	Germany	Wind and Solar	Jan 2010-Feb 2013	Day-ahead prices partially decreased due to renewable energy, but price effects varied over time, particularly for wind in the afternoon, evening, and night hours, and during the peak noon hours for solar.		Hourly day-ahead prices

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
Ballester and Furio (2015)	OLS model with Newey-West standard errors	Spain	Renewables (mainly wind)	2010-2013	They find a statistically negative relationship between renewable energy share and day-ahead market prices	The price volatility is modeled by a stochastic process with mean reversion that includes a discrete jump process (a diffusion model). Renewables significantly increase price volatility. However, the result is nuanced, for years 2002-2009 price volatility is higher, and jumps are more frequent during peak hours, from 2010 – 2013 when renewable generation is more relevant, just the opposite occurs.	Daily data averaged from hourly day-ahead data
Ederer (2015)	Simulation	Germany	Offshore wind	2006-2014	Short run -0.56 €/MWh for onshore, -0.75 €/MWh for offshore		Hourly spot market prices simulated

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
Gulli and Balbo (2015)	Hybrid analysis of simulation and ex-post empirical analysis (ex-post empirical analysis used to determine real impact on prices, simulation to determine merit-order and market power effects)	Italy	Solar	2010-2013	The impact of renewable energy sources on prices depends on market power as price decreases due to PV generation may be offset by firms pushing prices up when solar power is not available. Under market power, an increase in PV production can still provide benefits in terms of a wholesale price decrease by eroding residual market power for strategic conventional power firms. However, the average spot price during these periods (when firms exert market power) does not necessarily decrease.		Average hourly spot market prices weighted by zonal demands.
Swinand and O'Mahoney (2015)	Prais-Winsten regressions to correct for first-order serial correlation of the errors (AR1)	Ireland	Wind	2008-autumn 2012	1% increase in wind reduces system marginal price by about 0.06%, while each 1% wind forecast error increases system marginal price about 0.02%		30-min real-time system marginal price

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
Lunackova et al. (2017)	Prais-Winsten regression to correct for serial correlation in the errors and instrumental variables to correct for endogeneity due to supply of conventional resources (instrumenting for conventional generators' production with total production)	Czech Republic	Solar	2010-2015	Non-negative merit-order effect of solar		Hourly, daily, and weekly Day-ahead prices
			Other renewables	2010-2015	10% increase in other renewables (mainly water and wind) will decrease daily prices by 2.2%		
Janda (2018)	Multivariate regression estimated with both Newey-West standard errors and the Prais-Winsten estimator as a robustness check	Slovakia	Solar	2011-2016	A 1% increase in solar will decrease spot prices from 0.016% to 0.067%		Hourly day-ahead prices
de Lagarde and Lantz (2018)	Two-regime Markov switching model (see Section 8.0A.1.3A.1.3)	Germany	Wind	2014-2015	Decrease 0.77 EUD/MWh		Day-ahead hourly prices. Prices are transformed by applying the inverse of the hyperbolic sine function prior to analysis to compress extreme values
			Solar		Decrease 0.73 EUD/MWh		
Di Cosmo and Valeri (2018)	System of seemingly unrelated regressions where regressions are for each hour of the day	Ireland	Wind	2008-2012	0.018€/MWh when wind increases by 1 MWh (equivalent to 18€ per GWh)		Day-ahead hourly prices

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
Mountain et al. (2018)	Linear regression[1]	Australia	Wind	July 2012-June 2018	It shows that increasing the average wind generation by 100 MW would reduce the wholesale price by around $8.6/MWh throughout the year, though the precise value varies around the day, with summer price impacts most significant (but also most variable) around 3–6 p.m.		30-min spot prices
			Solar	July 2012-June 2018	It shows that a 100 MW increase in average PV production would reduce prices by around $11/MWh in summer and around $31/MWh in winter.		
Csereklyei et al. (2019)	Autoregressive distributed lag regression model	Australia	Wind	2010-2018	An extra GW of dispatched wind capacity decreases prices by 11 AUD/MWh An extra GWh of daily wind generation decreases daily average prices by 1 AUD/MWh		30-min and daily average prices
			Utility-scale solar	2010-2018	An extra GW of dispatched solar capacity decreases prices by 14 AUD/MWh		

[1] Note that Percy et al. (2018) extended the model of Bushnell and Novan (2018) which is intended to uncover long-term price effects of increasing amounts of VREs. However, the model (which was modified to add seasonal effects) was used to uncover short-term price impacts. The model did not include typical fixed effects that control for long-run trends (see our discussion of Bushnell and Novan 2018 for further information). The authors also did not discuss if any correlation was corrected for in the standard errors. We report the results but make note of these discrepancies.

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
Macedo et al. (2020)	A combination of Seasonal Autoregressive Moving Average with Exogenous Regressors (SARMAX) and GARCH and exponential GARCH methods (see Section A.1 for further detail)	Portugal	Wind	2017-2019	A 1% increase in wind decreases the wholesale prices by around 0.0568%	Significant positive impact on volatility (increase)	Day-ahead daily prices averaged over hourly data
			Wind	2011-2019	A 1% increase in wind decreases the wholesale prices by around 0.0598%		
			Solar	2017-2019	No significant impact	Significant negative impact on volatility (decrease)	
			Solar	2011-2019	A 1% increase in solar PV increases the whole sale prices by around 0.0001%		
Maciejowska (2020)	Quantile regression with autoregressive models (Models the distribution of prices, with a regression for each quantile of the distribution that includes exogenous and lagged price variables)	Germany	Wind and solar	2015-2018	Significant negative impact on the prices. The magnitude depends on time of day and load levels.	Volatility is quantified as inter-quantile range. Impact of renewable energy sources on daily volatility depends on the load levels. In peak hours, both wind and solar significantly reduce the price volatility, except for low load. On off-peaks hours, the impact is diversified.	Day-ahead daily prices averaged over hourly and peak and off-peak hours

Paper	Method	Country	VRE-type	Period	Reported Price Change[1]	Impact on Price Volatility	Price Data
Sirin and Yilmaz (2020)	Quantile regression with autoregressive models (Models the distribution of prices, with a regression for each quantile of the distribution that includes exogenous and lagged price variables)	Turkey	Wind	May 2016 - May 2019	1% increase in wind reduces market clearing prices by 0.01% - 0.15%, the strength of merit-order effect declines at the higher quantiles – which means as the day-ahead market clearing price increases, the merit-order effect from wind declines.		Hourly day-ahead prices (natural logarithms of prices are used to represent coefficients as elasticities)

2.2.1.2 Recommended Modeling Approach to Estimate VRE Impacts on Short-Term Energy Prices

Based on our review of the literature, we recommend a modeling approach to estimate the price impacts of VREs that both builds on and differs from the literature in important ways. First, the dominant modeling approach for U.S. markets is to include a lagged price variable as an explanatory variable to address the time-dependent nature of electricity price data. We recommend following this approach as we find past hourly prices an important predicator of current prices. A key difference in our recommended approach from much of the existing literature is that we recommend using panel data to incorporate fixed effects (time invariant unobserved variables) when controlling for observed and unobserved heterogeneity when estimating price effects from U.S. electricity markets. We also recommend that the effect of VREs on prices be evaluated over space and time to understand heterogeneous impacts. Last, we recommend the use of more recent electricity data to provide energy price impacts for markets in which solar and wind power have become a larger share of the generation mix than in previous studies.

To estimate the short-term impacts of increased levels of solar or wind resources on wholesale energy prices (the merit-order effect), we recommend that the modeling approach incorporate several variables to control for factors other than VREs that impact energy prices. Explanatory variables included in the model should be exogenously determined (i.e., not determined by the electricity market) to establish causality. As an example, because wind or solar power output generally depends on if the wind is blowing or the sun is shining, these variables are plausibly exogenous and should be included in the model.[1] Although power generation from other traditionally dispatchable resources (hydropower, gas, coal, and other fossil fuels) can cause price impacts because their dispatch can change in response to renewable energy production, including these variables can cause endogeneity concerns (see Woo et al. 2011). Instead, price impacts from shifts in the supply curve can be controlled for with the inclusion of a natural gas price variable, as a natural gas generator is typically the price-setting marginal generator in electricity markets, and natural gas prices are established in separate markets. Nuclear generation, as a baseload resource that typically does not respond to renewable energy production, can also be included. Other factors, such as the weather, are not determined by the electricity market, and therefore are plausibly exogenous and can be included in the model, although the effect of weather is typically included by controlling for electricity market demand, which historically, is plausibly exogenous due to its inelasticity.

A recommended model to determine the short-term impact of wind or solar generation on spot market prices is:

$$P_{t,i} = \alpha_t + \beta^l P_{t-1,i} + \beta^s Solar_{t,i} + \beta^w Wind_{t,i} + \beta^g NG_t + \beta^n Nuclear_{t,i} + \theta X_{t,i} + \varepsilon_{t,i} \quad (1)$$

Where *t* is the time index representing hour of day (h), day of month (d), or month of year (m). The ISO of the observation is indexed by i. $P_{t,i}$ is the average hourly real-time market price ($) in the relevant ISO. $P_{t-1}$is the lagged average hourly real-time market price of the previous hour for each ISO. $Solar_{t,i}$ and $Wind_{t,i}$ are hourly levels of wind or solar production (in MWh) for each

[1] Curtailment, on the other hand, could be endogenous and may need to be addressed through robustness checks to determine its impact on results. One possible method to address curtailment is an instrumental variable approach with curtailment and observed generation as instruments for wind or solar generation, as in (Bushnell and Novan 2018).

ISO. NG_t is the daily Henry Hub natural gas price to control for supply-related shifts from conventional generation that may be correlated with renewable production and demand. $Nuclear_{t,i}$ is the hourly nuclear generation for each ISO. $X_{t,i}$ includes hourly ISO load to control for price effects due to demand levels and other fixed effects. Hourly correlation between wind or solar output and demand that varies throughout the day is accounted for with hourly fixed effects. Differences in prices that may vary due to load variation by weekday or weekends is controlled for with day-of-week fixed effects. Long-run trends, such as changes in the generating resource portfolio over time and seasonality, are controlled for with month-by-year fixed effects. However, care must be taken in estimating this equation as it includes both a lagged variable (price) and fixed effects. Consistent estimation may require appropriate dynamic panel methods, depending on the panel structure.

We recommend the model in equation (1), when properly treated for consistent estimation, be estimated three ways: (1) as a pooled regression across all ISOs and hours to understand how VREs impact average real-time market price across all ISOs, (2) as a separate regression for each hour of the day to examine how VREs impact real-time market prices over time, and (3) by ISO to understand how VREs impact real-time market prices over space. Fixed effects should be updated as necessary to estimate each recommended model. Further, we recommend that additional analyses be performed to examine the robustness of results to the impact of outliers in individual ISOs (e.g., the sensitivity of results to transmission congestion, generator outages, out-of-market actions, and extreme weather events). Future work could also expand our recommended modeling approach to a more granular level within ISOs, examining nodal price impacts, to understand the local impacts of VREs.

2.2.2 Volatility Impacts from VREs

2.2.2.1 Literature Review

Though literature on the average behavior of electricity price and VRE penetration has been fairly consistent, its price volatility effects with respect to time (temporal price volatility) has been a topic of controversy. While some studies find evidence of an increase in temporal price volatility as VRE penetration increases (Woo et al. 2011; Astaneh and Chen 2013; Clò et al. 2015; Seel et al. 2018; Johnson and Oliver 2019; Mwampashi et al. 2020), others were unable to show any significant evidence that increasing the share of VRE leads to high temporal price volatility (Rai and Nunn 2020; Mulder and Scholtens 2013).

Rintamaki et al. (2017) found that, for the case of Germany and Denmark, increasing penetration of VRE could either increase or decrease the temporal price volatility. Shcherbakova et al. (2014) concludes in a wind energy study done for South Korea that temporal price volatility decreases as wind penetration increases up to 10% since the wind profile matches the demand patterns at this penetration. In a similar vein, many studies have found that solar energy penetration has abated temporal price volatility (Rintamaki et al. 2017; Pereira da Silva and Horta 2019). Further, there is evidence to suggest that the relationship between temporal price volatility and VRE penetration can vary widely as a result of a confluence of several factors, including (but not limited to) patterns of demand (Shcherbakova et al. 2014; Hirth 2018; Maciejowska 2020), weather (Mwampashi et al. 2020), and the availability of flexible generation (Rintamaki et al. 2017). Owolabi et al. (2021), also found that for five of the seven ISOs in their study (ISO-NE, NYISO,PJM, MISO, SPP, ERCOT and CAISO), the system temporal price volatility decreased as the penetration of VRE increased across all quantiles. These results are consistent with the modern portfolio theory that posits that the portfolio of diverse and uncorrelated (or low correlated) assets leads to price volatility reduction (Markowitz 1952).

2.2.2.2 Determinants of Volatility in Electricity Markets

When modeling the impact of VREs on electricity price volatility, there is a need to first understand (a) the importance of quantifying volatility in electricity markets and (b) what drives price volatility in electricity markets.

Since the first decade of the 21st century, with the electricity industry evolving in to a more distributed and competitive industry, researchers have been paying more attention to the volatility of asset and energy prices (Cifter 2013). In the emerging competitive environment, producers and buyers not only need to forecast future electricity prices, but also need to assess the risks of electricity prices; the most accurate way to quantify risks in electricity prices over a period is by simulating electricity price volatility (Deb et al. 2000).

According to Li et al. (2019), there are two approaches in the literature when it comes to explaining volatility in electricity markets. One approach involves attributing volatility to the occurrence of extremely high price records (i.e., spike prices, which indicate an increase in demand). In Hadsell and Shawky (2006), the focus is on high prices during peak hours, with the intent of examining the volatility characteristics of NYISO electricity markets. They find evidence to link the occurrence of spike prices with market price volatility. Joskow and Wolfram (2012) and Dutta and Mitra (2017) discuss candidate technologies that could dampen spike prices and control volatility.

Another approach in the literature is to focus on negative pricing (a distinctive feature of electricity markets) as a source of price volatility in electricity markets. Negative pricing arises because certain types of generators (e.g., nuclear, hydroelectric, and wind energy) pay load serving providers to take power instead of lowering their output due to technical and economic factors during a shortfall in demand (EIA 2017). Genoese et al. (2010) found evidence that suggests that negative pricing has an upward (increasing) trend and an unbalanced distribution for the case of the German markets, and it increases price volatility. Barbour (2014) highlights the role of negative pricing in the development of technologies like energy storage.

Using a principal components analysis, Li et al. (2019) concluded that components with the largest explanatory power (to the variation of prices) are highly related to spike LMPs and the position and the extent of concentration of the overall LMPs. Further, using a nonlinear autoregressive distributed lags model (NARDL), they concluded that negative prices have a larger potential effect on both the real-time market and the forward market. An implication of this finding is the potentially stabilizing role of renewable energy on the energy demand.

In the literature, different metrics have been used to measure price volatility in the market for electricity. Table 5 documents a few of these.

Table 5. Electricity Market Price Volatility Indicators[1]

Author	Name of Indicator	Equation	Assessment of value indicator
Danilenko (2007)	Dispersion	$\sigma^2 = \frac{1}{n-1}\Sigma_{i=1}^{n}(x_i - \overline{x})^2$	The higher the value, the more volatile the electricity price is
Wolak (1998)	Standard Deviation	$\sigma = \sqrt{\sigma^2}$	
Lucia and Schwartz (2002)	Standard Volatility	$V = \sigma\sqrt{365}$	
Munoz and Dickey (2009)	Square of difference of two neighboring values	$V = (x_t - x_{t-1})^2$	
Paulavičius (2010)	Coefficient of oscillation	$K_R = \frac{x_{MAX} - x_{MIN}}{\overline{x}} * 100\%$	
Bobinaite (2011)	Coefficient of variation	$V = \frac{\sigma}{\overline{x}} * 100\%$	Up to 10%: low variation 10%-20%: medium variation 20%-30%: high variation >30%: very high variation
Li and Flynn (2004); Zareipour et al. (2007)	Daily velocity indicator, calculated under the average price of electricity during a day	$DVOA_{iP} = \frac{\frac{1}{M}\left(\Sigma_{j=1}^{M-1}\left\|P_{i,j+1} - P_{ij}\right\| + \left\|P_{i-1,M} - P_{i1)}\right\|\right)}{\left(\frac{1}{M}\right)\Sigma_{j=1}^{M}\ P_{ij}}$	The higher the value, the more volatile electricity price is
	Daily velocity indicator, calculated under the average price of electricity during a certain time period	$DVOA_{iP} = \frac{\frac{1}{M}\left(\Sigma_{j=1}^{M-1}\left\|P_{i,j+1} - P_{ij}\right\| + \left\|P_{i-1,M} - P_{i1)}\right\|\right)}{\left(\frac{1}{M*N}\right)\Sigma_{i=1}^{N}\Sigma_{j=1}^{M}\ P_{ij}}$	

2.2.2.3 Volatility Modeling Approaches

In this section, we will provide a brief background on volatility models that are typically used to assess the impact of VREs on price volatility. Before we delve in the to the model related technicalities, we will first discuss stylized facts that need to be considered for the commodity under consideration when modeling volatility.

According to Engle and Patton (2007), although a volatility model is generally used to forecast the absolute magnitude of returns, it may also be used to predict quantiles or, in fact, the entire density of the distribution of returns. In the financial domain, such forecasts are used in risk management, derivative pricing, and many other financial activities. For each of these

[1] This table is reproduced from Bobinaite et al. (2012).

applications, it is the predictability of volatility that is of paramount importance. A risk manager needs to know *today* what the likelihood is of their portfolio declining in the future. And in order to hedge this risk, they will need information on the volatility of this forecast.

There are two general classes of volatility models in widespread use. The first of these formulates the conditional variance directly as a function of observables. Examples include the autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models. The second (latent volatility or (misleadingly) stochastic volatility models) involves models of volatility that are not functions purely of the observables. While such models can typically be simulated, they are difficult to estimate and forecast.

A number of stylized facts about the volatility of electricity prices have been documented in the literature. According to Engle and Patton (2007), a good volatility model must be able to capture and reflect these stylized facts. These stylized facts include the following. Electricity is characterized by a high volatility due to current storage limitations; this is attributed in part to the fact that deployment of storage technology remains limited. In the context of renewables, **the intermittent nature of output from VREs will be transferred to electricity prices, resulting in increased uncertainty and, hence, greater price volatility and price risk (**Ballester and Furió 2015), although this may be mitigated with future deployments of storage technologies. According to Masoumzadeh et al. (2017), storage technologies, their forms notwithstanding (pump-storage hydro, large-scale, or distributed batteries), are capable of alleviating the extreme price volatility levels on account of their energy usage time shifting, fast-ramping, and price arbitrage capabilities.

Additionally, the intermittency of VRE generation, when compared to conventional power sources such as nuclear or fossil fuels, is one of the main arguments proffered to explain why prices should become even less predictable, and hence even more volatile, as long as generation from VREs increases. In addition, it is **this intermittency that may lead to increases in both the number and magnitude of the so-called price jumps (**Ballester and Furió 2015). Byström (2005) applied conditional extreme value theory to investigate the hourly spot price volatility of the Nordic electric power market and concluded that not only are price changes highly volatile, but their empirical distribution is highly non-normal (pointing to the usefulness of conditional volatility models for price volatility forecasts). Electricity prices also exhibit asymmetric characteristics, where positive shocks to the price series have less effect on the conditional variance compared to negative shocks[1] (Schulueter 2010; Karandikar et al. 2009).

As an example, Ballester and Furió (2015), using a model adapted from Cartea and Figueroa (2005), set out to measure the extent to which VRE generation may be behind price volatility and how the share of renewable energy volatility contributes to the presence of price jumps for the Spanish market find the following:

The price volatility is higher for off-peak than for peak hours (0.15 versus 0.9). In addition, the frequency of price jumps is also notably higher for off-peak hours, whereas the mean reversion is not much lower, as indicated by the value of the α coefficient (Figure 12 and Figure 13). Figure 12 shows the evolution of jumps (note: Y is a diffusion process with jumps and mean

[1] This asymmetric effect is frequently referred to as the “leverage effect.” Conditional variances are the characteristics of variability of conditional distributions (i.e., the variance of prices given the values of one or more other variables).

reversion of the spot prices) throughout the years in the sample. The large jumps (between January and May in 2010 and in 2013) in Figure 12 correspond to increasing volatility during these two periods (Figure 13); this was even more noticeable during off-peak hours.

In Figure 14, for the two periods with the greatest price volatility—from January to May 2010 and from January to May 2013—volatility peaks in HI (hydraulic), NUC (nuclear), and BG (pumped hydro) generation match marginal price volatility peaks better than renewable energy. This seems to imply that (for this study) the volatility of the electricity produced by the different generation technologies has been transferred to prices.

Negative jumps are much more frequent than positive for baseload (62 versus 33), peak (38 versus 16), and off-peak (75 versus 40) hours.

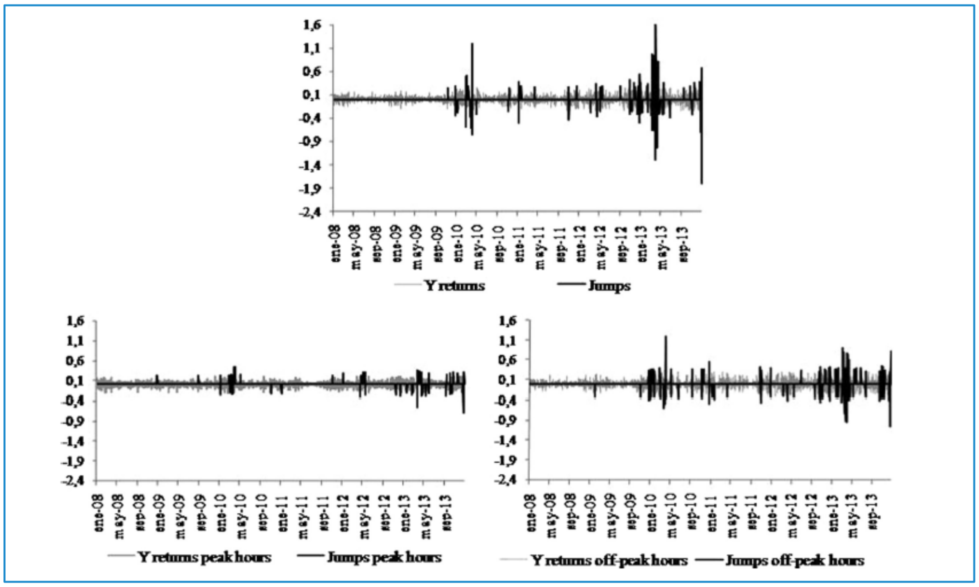

Figure 12. Price without Seasonal Component (Y) in Returns and Jumps Detected (2008–2013)

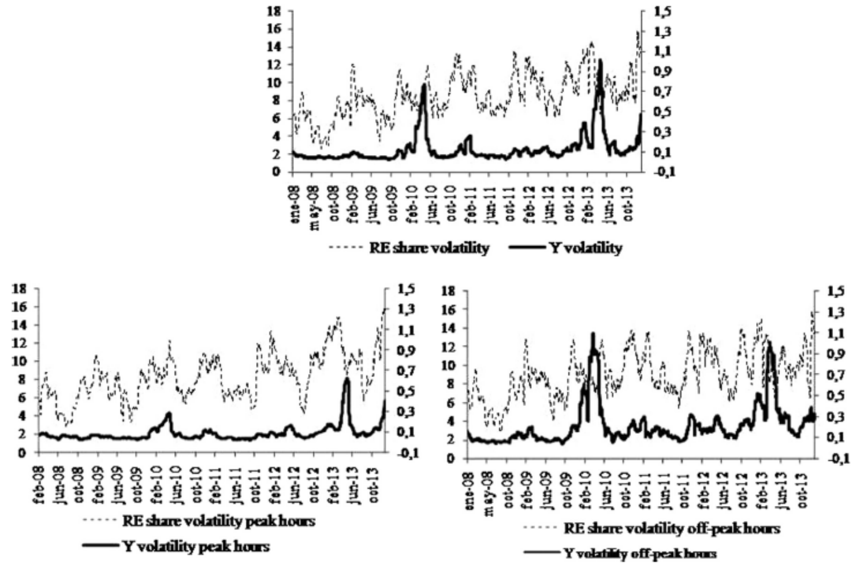

Figure 13. RE Share Volatility and Base Load Marginal Price without Seasonal Component (y) Volatility

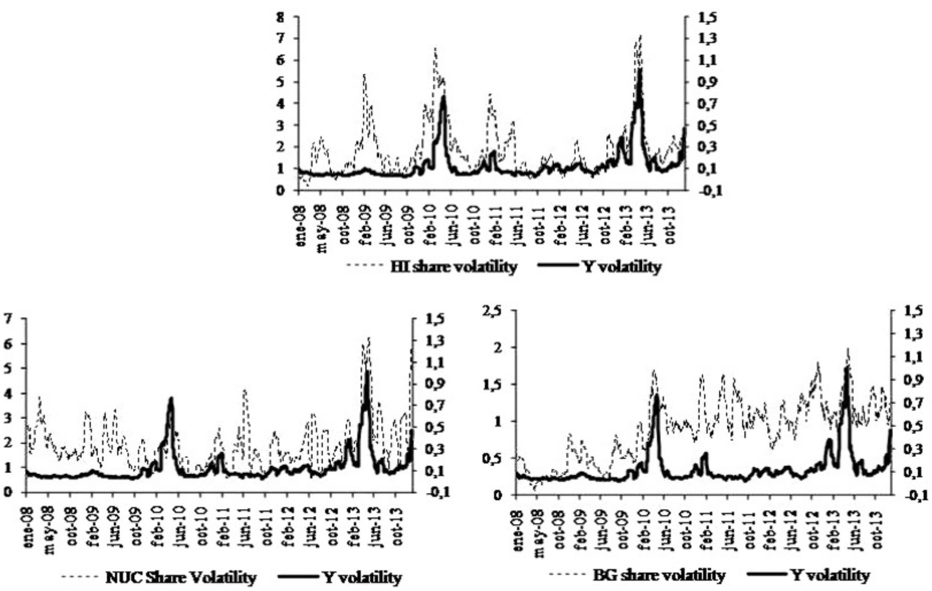

Figure 14. Base Load Marginal Price without Seasonal Component (y) Volatility, Hydraulic Share (HI) Volatility, and Pumping Hydroposer Share (BG) Volatility

In the context of the Australian market, however, Rai and Nunn (2020) concluded that higher penetration by VRE generation may not result in more extreme price jumps or higher market price caps. They cite the following reasons in support of their conclusions: (1) greater investment in volatility-dampening, reliability-enhancing technologies like storage and interconnectors, (2) increased contract cover, (3) more price-responsive demand, and (4) emergence of additional ancillary service revenues.

In Appendix A, we have provided detail on the different approaches that are used to model volatility along with example applications to the electricity markets.

2.2.2.4 Recommended Modeling Approach for Modeling VRE Impacts on Electricity Price Volatility

Many approaches have been used in the literature to model volatility in electricity prices. However, given that (a) electricity price changes are highly regime dependent[1] and (b) price changes follow a non-normal distribution, we propose a combination of a Markov switching and a GARCH model to determine volatility impacts from VREs.

Cifter (2013) used a Markov switching (MS) GARCH model to forecast volatility for the Nordic electric power market. Electric prices are not only highly volatile but also regime dependent (i.e., they are prone to extreme jumps). Additionally, they are also known to exhibit asymmetries; positive shocks to the price series have a lesser effect on the conditional variance compared with negative shocks (Schlueter 2010; Karandikar et al. 2009). While both time series (e.g., autoregressive integrated moving average (ARIMA), GARCH) (Contreras et al. 2003; Garcia-Martos et al. 2007; Garcia et al. 2005) and artificial models (e.g., neural networks, fuzzy neural networks) (Wang and Ramsay 1998; Cataloa et al. 2007; Vahidinasab and Kazemi 2008; Hong and Lee 2005; Amjady 2006) have been used to forecast short-term electricity prices, one major drawback of all of these approaches is their inability to capture extreme jumps or 'regime changes' as prices increase/decrease sharply in the short run. This, in turn, calls for models that are capable of capturing regime changes and asymmetries, thus making the case for an MS-GARCH type model. The parameter changes between a low and high regime that is allowed for in this modeling approach enables more accurate forecasting.

Following Cifter (2013), our proposed approach is as follows:

I. The GARCH model:

To account for the asymmetries in the observed prices, we propose to estimate a Glosten-Jagannathan-Runkle (GJR)-GARCH model (which has demonstrated superior forecasting performance than the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model for longer horizons). The model may be expressed as follows:

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma \alpha_1 \epsilon_{t-1}^2 I_{t-1} + \beta_1 h_{t-1} \tag{2}$$

where α_0 is the constant term, $\frac{\epsilon_t}{\psi_{t-1}} \sim N\left(0, \sqrt{h_t}\right)$ denotes the conditional volatility of $\sqrt{h_t}$ with the conditions of ϵ_t and $\alpha, \beta > 1$, $\alpha_0 > 1, \gamma^2$ is a dummy variable that takes on the following values: $I_{t-1} = 1, if\ \epsilon_{t-1} < 0, I_{t-1} = 0$, otherwise. In the GJR model, negative lagged shocks have an impact of $\alpha_1 + \gamma$ while positive lagged shocks have an impact of α_1, implying that the former have a bigger influence on conditional variance.

II. The Markov switching model

The realization of a two regime Markov chain can be expressed as follows:

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[1] Time series models typically have 'a' set of model parameters that can be used to describe the behavior of the data over time. This assumption is not valid in the real world, however, since real world time series data may have different characteristics (such as means and variances) across different time periods (or "regimes"). Electricity price changes are highly dependent on the underlying model parameters that characterize the regime in operation – hence the term, 'regime dependent'.

[2] The electricity price return, r_t, refers to continuously compounded return of the assets.

$$P\{s_k = j | s_{k-1} = i, s_{k-2} = k, \ldots\} = P\{s_k = j | s_{k-1} = i\} = p_{ij} \tag{3}$$

Where p_{ij} denotes the probability of moving from regime i to regime j. If s_k follows a two regime Markov chain with transition probabilities, this can be defined as follows:

$$\Pr[s_k = 0 | s_{k-1} = 0] = p,$$

$$\Pr[s_k = 1 | s_{k-1} = 0] = 1 - p\,,$$

$$\Pr[s_k = 1 | s_{k-1} = 1] = q,$$

$$\Pr[s_k = 0 | s_{k-1} = 0] = 1 - q \tag{4}$$

Where $s_k = 0$ represents the normal (low) volatility regime and $s_k = 1$ represents the jump regime.

III. The Markov switching-GARCH model

The MS-GARCH model can then be represented as follows:

$$h_t = \left[\alpha_0 + \alpha_{1(s_t)}\epsilon_{t-1}^2 + \beta_{1(s_t)}h_{t-1}\right]I[s_t = 0] + [\alpha_0 + \alpha_{1(s_t)}\epsilon_{t-1}^2 + \beta_{1(s_t)}h_{t-1}]I[s_t = 1] \tag{5}$$

Where $s_t = 0$ represents the low volatility regime and $s_t = 1$ represents the high volatility regime.

The MS-GARCH approach entails the estimation of the high and low volatility structures of electricity prices, while also accounting for the observed asymmetries. Given that electricity prices are highly regime dependent, some form of a Markov switching model that allows for regime changes needs to be deployed. Additionally, GARCH type models are known to be capable of addressing asymmetries[1] in the observed data. Under the circumstances, some combination of an MS-GARCH type model that has the ability to capture both regime changes and asymmetries needs to be adopted to model volatility in electricity prices.

2.2.3 Ancillary Service Price Impacts

Increased price volatility translates to more periods with high prices and more periods with negative prices in electricity markets with higher penetrations of VREs. Under these conditions, pricing becomes more important to align resources with where they are valued most, based on the operating conditions. As was described in Section 2.1.1, in U.S. markets this is typically accomplished with shortage pricing on operating reserves, to incentivize resources to produce and sell power when it is needed most. Some markets—ERCOT and PJM—have implemented ORDC approaches to better align price incentives with the value of operating reserves under

[1] In the context of electricity prices, as mentioned before, asymmetries of the following form are known to exist - positive shocks to the price series have lesser effect on the conditional variance compared with negative shocks (Schlueter 2010; Karandikar et al. 2009).

different operating conditions. Papavasiliou (2020) points out that increasing levels of VREs require electricity markets to increasingly rely on operating reserves.[1]

Ancillary services encompass several reliability resources needed for addressing supply and demand imbalances in real-time, including regulation of frequency, energy imbalance, spinning operating reserve, and supplemental operating reserve, as well as voltage control and system restoration services (Stoft 2002; Creti and Fontini 2019). In the United States, markets differ in their nomenclature for these services as well as remuneration of these services. However, all markets procure the following services through competitive markets: regulation reserves, spinning reserves, and non-spinning reserves (Kahrl et al. 2021). All markets procure the following services on a cost basis through bilateral arrangements: voltage support and black start capability (Kahrl et al. 2021).

Both spinning and non-spinning reserves protect the system from contingencies such as unplanned generator outages or wind or solar forecast errors. Regulation reserves respond within seconds to keep supply and demand in balance. Requirements for system-wide ancillary services are typically designed to meet North American Electric Reliability Corporation (NERC) reliability requirements and performance standards. Regulation reserve quantities are generally based on net load variability, spinning and non-spinning reserve on inertia conditions, and forecast errors; therefore, the reserve requirements vary hourly (Ghosal et al. 2022). Important for our research, reserve requirements are determined by load variability, potential generator outages, and forecast errors.

When procurement of energy and ancillary services are co-optimized in the day-ahead or real-time market, resources do not need to estimate the tradeoff between providing capacity for energy versus ancillary services. This tradeoff is reflected in the market, allowing each resource to bid all of its capacity into the energy and ancillary service markets, without risking revenue loss in one market if capacity is sold in the other (CAISO 2020). With co-optimization, expectations of foregone energy sales are not included in ancillary service capacity offers, allowing ancillary service clearing prices to account for the opportunity cost of selling energy (Potomac Economics 2021a). Without co-optimization, resources estimate the opportunity costs between providing energy or ancillary services. Expectations over energy market prices and fuel costs (especially natural gas) will inform these bids. Important for our research, in markets with co-optimized energy and ancillary service procurement, energy and ancillary service prices will likely be correlated. The market clearing price resources receive for providing ancillary services typically reflects their capacity bids and opportunity costs, with regulation resources typically receiving higher payments than spinning reserves and spinning reserves receiving higher payments than non-spinning reserves (Kahrl et al. 2021).

Table 6 highlights ancillary service procurement and pricing processes in CAISO, ERCOT, and ISO-NE ancillary service markets.

[1] A real-time market for reserve capacity does not exist in Europe. Papavasiliou (2020) recommend an ORDC, as applied in some U.S. markets, as a solution to this problem.

Table 6. Ancillary Service Procurement and Pricing Processes

	CAISO	ERCOT	ISO-NE
Ancillary services	Four types of Ancillary Services are procured in CAISO day-ahead and real-time markets (CAISO 2022): ▪ Regulation Up ▪ Regulation Down ▪ Spinning Reserve ▪ Non-Spinning Reserve CAISO procures Flexible Ramping Up and Flexible Ramping Down in the real-time markets (15- and 5-minute markets)	Four types of Ancillary Services are procured in ERCOT's day-ahead and supplemental ancillary services markets (Potomac Economics 2021a): • Regulation Up • Regulation Down • Responsive Reserve • Non-Spinning Reserves	Four types of Ancillary Services are procured in ISO-NE's markets (ISO-NE 2022): • Regulation • 10-Minute Spinning Reserve • 10-Minute Non-Spinning Reserve • 30-Minute Operating Reserve • Local 30-Minute Operating Reserve
Ancillary service requirements	The regulation capacity requirement is based on inter-hour changes in scheduled generation, intertie schedules, forecasted demand, and the number of units starting up or down. The operating reserve requirement is set by the maximum of 5% of forecasted demand met by hydroelectric resources plus 7% of the forecasted demand met by thermal resources (or the largest single contingency) (CAISO 2010). 100 % of the expected reserve requirement is purchased in the day-ahead market. Reserve requirements can change in real-time depending on system conditions. In 2020, regulation down requirements were 520 MW, regulation up requirements were 390 MW, and average combined requirements for spinning and non-spinning reserves were about 1,800 MW.	Responsive reserve requirements are based on a variable hourly need. Regulation reserve quantities are generally based on net load variability, responsive reserve on inertia conditions, and non-spinning reserve on forecast errors. The combination of regulation reserves and non-spinning reserves cover up to 95% of the net load forecast error, and non-spinning reserves are procured at a quantity greater than or equal to the largest generation unit during on-peak hours. In 2020, the average total ancillary services requirement was 4,800 MW, but the quantity of reserves held varies by hour.	The ISO maintains sufficient reserves to recover from the largest single system contingency within 10 minutes, additional reserves must be available within 30 minutes to meet ½ of the second-largest system contingency, local resources are identified to meet second-contingency requirements in import-constrained areas. In 2020, the average 10-minute spinning reserve requirement was 527MW, the average total 10-minute and 30-minute reserve requirements were 1,700 MW and 2,500 MW, respectively.
Ancillary service procurement	CAISO has a co-optimized procurement of energy and ancillary services in day-	ERCOT has a co-optimized procurement of energy and ancillary	ISO-NE procures reserves six months ahead (but not day-ahead) in the forward

	CAISO	ERCOT	ISO-NE
	ahead and real-time markets. Procurement of flexible ramping products are co-optimized with energy and ancillary services in the real-time markets.	services in the day-ahead market. Additional reserves are procured in the supplemental ancillary services market (at much higher prices). Co-optimization of energy and ancillary services in the real-time market is planned for 2025 and will replace the need for a supplemental ancillary services market.	reserve market auction and co-optimizes energy and operating reserve procurement in the real-time market, real-time regulation services are procured in the regulation market.
Ancillary service pricing	Resources providing ancillary services receive a capacity payment at market clearing prices for both day-ahead and real-time markets. Regional ancillary service shadow prices reflect the cost of having to procure one additional megawatt of a particular service within a given region. The market clearing price is the summation of the regional ancillary service shadow prices for that service in the regions where a resource resides.	ERCOT has a single region for ancillary services. In the day-ahead market, ERCOT establishes the Ancillary Services Plan for ancillary service requirements the following day. Qualified scheduling entities submit bids and offers for ancillary services, which are cleared to determine the market clearing price for ancillary service capacity.[1] In the real-time market ERCOT will apply price adders if reserves are insufficient.	The forward reserve market is used to acquire commitments from resources months in advance to provide real-time reserve capacity. Forward reserve capacity requirements (demand) are based on the forecasted first- and second-contingency supply period. Forward reserve auction clearing prices are calculated for each reserve service, for each reserve zone.[2] The real-time reserve market is used to offset opportunity costs when a resource provides reserve capacity instead of producing electricity

[1] Note that the objective function for the secure economic dispatch (SCED) is the sum of four components: (1) the cost of dispatching generation; (2) the cost of procuring Ancillary Services; (3) the penalty for violating Power Balance constraint and (4) the penalty for violating network constraints, which allows the SCED to economically dispatch resources and procure ancillary services.

[2] As an example, a forward reserve resource will receive revenue from the forward reserve auction but forego real-time reserve payments and energy revenue in most hours, as this resource will be held in reserve.

	CAISO	ERCOT	ISO-NE
Scarcity pricing	CAISO administratively sets the scarcity price with a scarcity pricing demand curve when ancillary services' supply is insufficient to meet demand	ERCOT applies real-time ORDC price adders which approximates the pricing outcome of real-time energy and ancillary service co-optimization since the price adder captures the value of the opportunity cost of reserves based on the ORDC (ERCOT 2021)	The real-time reserve pricing market is used to compensate market participants for the increased value of their production when the system is short of reserves

2.2.3.1 Literature Review

Limited empirical analyses have been conducted on the impact of VREs on operating reserves, frequency regulation, or scarcity pricing. While not focused specifically on the impact of increasing levels of VREs, Zarnikau et al. (2019) explored determinants of ancillary service prices in Texas, finding that ERCOT's day-ahead prices for ancillary services increase with energy prices and ancillary service procurement forecasts, but decline with ancillary service offer forecasts. Because wind generation decreases ERCOT's energy prices, Zarnikau et al. (2019) point out that Texas can reduce prices for day-ahead ancillary services through wind generation development. Wiser et al. (2017) came to the opposite conclusion; using a simulation modeling approach, they found that increasing amounts of renewables increased ancillary service prices (while decreasing wholesale prices).

Di Cosmo and Valeri (2018) examined the impact of renewables on both energy prices and balancing payments in Ireland from 2008 through 2012. Using a seemingly unrelated regression approach, they determined that although 1 MWh of wind energy caused declines in wholesale energy prices of 0.018€/MWh, it also increased constraint payments by 3.2€/MWh. Batalla-Bejerano and Trujillo-Baute (2016) found that renewables increase ancillary service and other balancing costs in Spain, whereas Gianfreda et al. (2016) and Hirth and Ziegenhagen (2015) found that renewables decrease ancillary service and other balancing payments in Italy and Germany, respectively.

In theory, rising levels of renewables may increase the demand for ancillary services as balancing the intermittency of renewable requires more flexible services; however, this increase can be mitigated by better renewable power production forecasting and increased demand flexibility (Pollitt and Anaya 2020). Further complicating the issue is that rising demand for ancillary services may not necessarily indicate a rise in prices for ancillary services as distributed generation could potentially supply those services at a lower cost. Highlighting the importance of regulation for ancillary service prices, Frew et al. (2021) found that operating reserve scarcity pricing rules are instrumental to both energy and ancillary service market outcomes, as energy and reserve prices are both strongly impacted by scarcity pricing events. However, the literature has yet to come to a consensus on how increasing amounts of renewables will impact ancillary service prices.[1]

[1] For a review of the literature on analyses of ancillary service market prices (not specific to price impacts of VREs) see Pollitt and Anaya (2020).

2.2.3.2 Recommended Modeling Approach for Estimating Ancillary Service Price Impacts from VREs

Our recommended modeling approach for estimating VRE price impacts on ancillary services builds on the literature by recognizing that demand for ancillary services is driven by load variability, potential generator outages, and wind or solar forecast errors.

$$Q_{AS} = f(load\ variability,\ generator\ outages,\ wind\ or\ solar\ forecast\ errors)$$

In a market without co-optimization of energy and ancillary services, supply of ancillary services depends on expectations of energy market prices (opportunity costs) and fuel costs. However, with co-optimization, a resource does not need to explicitly consider its opportunity costs.

$$S_{AS} = f(energy\ market\ price\ \exp e\ ctations;\ fuel\ costs)$$

To capture these fundamental drivers, we propose the following model for real-time ancillary services price impacts:

$$\begin{aligned} AS_{t,i} = \alpha_t + \beta^s Solar_{t,i} + \beta^{se} SolarError_{t,i} + \beta^w Wind_{t,i} + \beta^{we} WindError_{t,i} + \beta^g NG_t \\ + \beta^l LoadVar + \beta^o Outage + \theta X_{t,i} + \varepsilon_{t,i} \end{aligned} \tag{6}$$

Where t is the time index representing hour of day (h), day of month (d), or month of year (m). The ISO of the observation is indexed by i. $AS_{t,i}$ is the average hourly price for ancillary services (operating reserves, regulation up, regulation down) in $/MWh in a selection of ISOs with co-optimized day-ahead and real-time markets. $Solar$ is the actual hourly solar production and $SolarError$ and $WindError$ follow the same methodology, but for wind production and wind forecast errors. NG is the daily Henry Hub natural gas price to control for supply-related shifts from conventional generation that may influence ancillary service offers. $LoadVar$ is the hourly load variation measured as the standard deviation of load for that hour. $Outage$ is a variable representing planned generator outages. X includes hourly ISO load to control for price effects due to demand levels as well as a measure of excess capacity by balancing authority available to meet peak load from FERC Form 714 Schedule II Part 1. We will include hour-of-day fixed effects, day-of-week fixed effects, and month-by-year fixed effects to account for confounding trends. Errors can be clustered at the ISO level or use another error correction for potential heteroskedasticity and autocorrelation in the errors.

To address that energy and ancillary services markets are interrelated, especially in co-optimized markets, a seemingly unrelated regression can be applied to the short-term energy price impact equation (1) and the AS equation (6). By weighting the covariance in residuals from equations (1) and (6), seemingly unrelated regression can produce more efficient estimates.

In future research, we aim to estimate the impacts of VREs on ancillary services to understand how increasing amounts of VREs affect this important revenue stream.

2.2.4 Capacity Price Impacts

Even with revenues from both energy and ancillary service markets, power producers may fall short of obtaining the revenue necessary to cover their fixed and operating costs. In most wholesale electricity markets today, this revenue shortfall is addressed through capacity payments or a capacity market. However, increasing amounts of VREs can also affect capacity payments and capacity market prices. Further, increased price volatility from VREs can affect a risk-averse investor's willingness to purchase forward contracts for capacity.

2.2.4.1 Literature Review

Byers et al. (2018) found that capacity markets across the United States[1] have large differences in capacity market design and mechanisms, including incentives for operational performance, methods to calculate qualifying capacity for VREs and storage, and methods to calculate demand curves for capacity. Further, differences in capacity market design and mechanisms have led to large differences in historical capacity market clearing prices across markets. Particularly important to VREs is the approach used to calculate the qualifying capacity of VREs and energy storage.

In U.S. capacity markets, allowable capacity market bids are based on a resource's unforced capacity, which is typically estimated from a resource's installed capacity derated for expected outages based on prior period performance (Byers et al. 2018). The value of the qualifying capacity differs by market and by resource type. As an example, Table 7 provides an overview of different approaches to wind and solar qualifying capacity valuation across a selection of ISOs. Historically, markets used a resource's actual performance (power production) during certain hours (peak loads or shortage conditions). However, in recent years, many markets have moved to an effective load carrying capability (ELCC) approach.[2] With this approach, each resource's qualifying capacity is based on the incremental demand it can reliably serve, while also considering the probability of demand not being served (LOLE) for various reasons, including generator outages and shortfalls.[3] ELCC measures each resource's contribution to the resource adequacy needs of the entire system. Regardless of the calculation method, the qualifying capacity affects a resource's bid as well as expected performance (and any penalties it may pay for non-performance) in markets with formal capacity markets and performance incentives.

Table 7. Qualifying Capacity Valuation

ISO	Capacity Mechanism	Wind/Solar Qualifying Capacity Values
CAISO	CAISO's resource adequacy programs have deliverability criteria that each load serving entity must meet as well as rules for counting resources that must be made available to the ISO. Monthly capacity prices are paid by (or to) load serving entities based on resource adequacy capacity contracts (CPUC 2022a).	Wind and solar qualifying capacity values are based on ELCC modeling. The California Public Utilities Commission (CPUC) periodically updates the ELCC values (CPUC 2022a).

[1] These include centralized capacity markets in PJM, ISO-NE, MISO, and NYISO.
[2] ELCC is used to calculate the capacity value for wind resources in MISO; for intermittent resources, storage, and hydro in PJM; for intermittent resources in CAISO and SPP; and for energy storage in NYISO.
[3] The ELCC is estimated based on historical and simulated data, see MISO (2020) for further detail.

ISO	Capacity Mechanism	Wind/Solar Qualifying Capacity Values
ERCOT	Wind and solar capacity contribute to ERCOT's planning reserve margin as a capacity resource available to meet peak load. Because ERCOT is an energy only market, there are no revenue contributions from an installed capacity market, as such energy and reserve prices provide the only funding for revenue sufficiency.	Existing wind (solar) capacity is calculated as the capacity available for summer and winter peak wind (solar) by year by region, multiplied by the seasonal peak average wind (solar) capacity as a percent of installed capacity. The seasonal peak average wind (solar) capacity as a percent of installed capacity is the average wind (solar) generation resource capacity, calculated as the average capacity during the 20 highest system-wide peak load hours, available for summer and winter peak load, divided by regional installed capacity. The final value is the weighted average (by capacity) of the previous ten eligible years (for wind) or three eligible years (for solar) of seasonal peak (ERCOT 2022).
ISO-NE	Qualified VREs can participate in ISO-NE's mandatory, centralized capacity market, the Forward Reserve Market (ISO-NE 2021; ISO-NE 2022).	Wind/solar qualifying capacity is based on a resource's median output during predetermined "reliability" hours (average over five years, during hours when loss -of-load is a potential risk) (ISO-NE 2021).

For example, for the 2021–2022 planning year, MISO determined the system-wide capacity wind credit to be 16.3%. As they apply the ELCC value to all wind resources in their market footprint, of 22,040 MW of installed wind capacity, 3,598 MW (22,040 MW*16.3%) potentially qualifies for resource adequacy (MISO 2020). Because the amount of power that VREs can produce in peak conditions is highly variable and uncertain, in 2020, MISO's market monitor recommended that an ELCC methodology be developed for solar, battery, and distributed energy resources (Potomac Economics 2021b). However, the ELCC approach can also degrade reliability if assumptions do not reflect market realities (Monitoring Analytics 2021). To that end, in a simulation of the electricity market in Texas, Bothwell and Hobbs (2017) found that inaccurate capacity credits for wind and solar resources both increase costs and shift investment among technologies, leading to market inefficiencies.

The ELCC method also captures an interesting feature of the capacity value of VREs—additional resources do not always equal additional reliability. Figure 15 displays the ELCC for wind and Figure 16 displays the ELCC for solar from PJM's ELCC report. Both ELCC figures show projected ELCCs from 2023 through 2031 with increasing penetrations of wind and solar resources. The trend that as VRE penetration goes up, ELCC goes down (marginal contribution of incremental VRE capacity goes down) reflects the decreasing marginal reliability benefits of VREs. For example, the first unit of a solar resource added to the grid significantly increases reliability. But as incremental amounts of solar resources are added to the grid, reliability issues can be pushed to other hours when solar is not online, decreasing reliability benefits. However, there are also diversity benefits if, for example, wind resources address reliability issues in the evening and night hours.

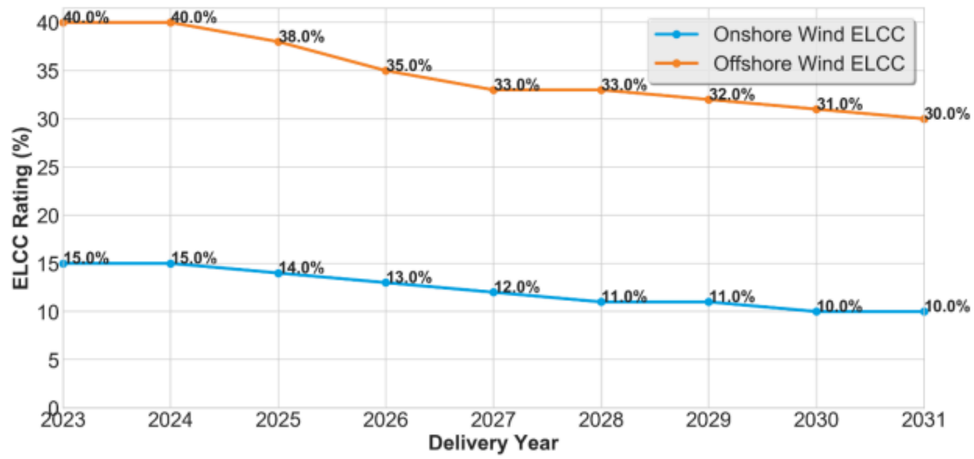

Figure 15. ELCC Ratings for Onshore and Offshore Wind in PJM. Source: PJM.

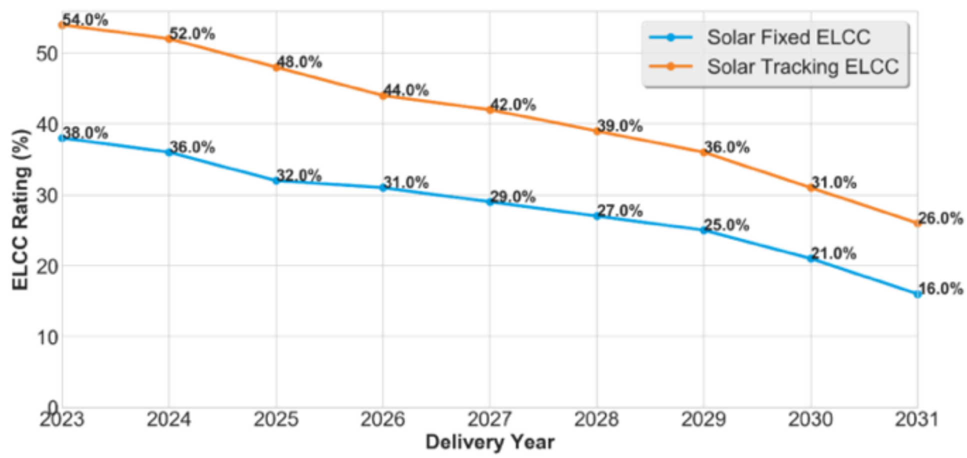

Figure 16. ELCC Ratings for Fixed and Tracking Solar Panels in PJM. Source: PJM.

The declining marginal benefit of wind or solar power for reliability echoes a similar finding in the literature on the value of wind or solar resources. Prol et al. (2020) found that increasing amounts of wind and solar resources in California undermine revenues not only for conventional generating resources, but also for other wind and solar resources. Further, Bushnell and Novan (2018) found that the varying value of VREs can also affect investment. Because increased solar capacity reduces midday prices, the marginal revenue from additional solar capacity investments diminishes. For example, the tenth gigawatt of California's grid-level solar capacity has half the marginal revenue of the second gigawatt of capacity.

Increasing amounts of VREs can also cause increased variability in energy prices. For investors, this increases the risk that their investment will earn its required return. With many potential market designs available to address the missing money problem in electricity markets, how well investors can manage risk is also an important consideration for incentivizing appropriate investment. Petitet et al. (2017) examined how a capacity mechanism (scarcity prices or capacity payments) can address supply security objectives under increasing levels of

VREs. To address this question, they conducted a simulation of a power market. They found that in an energy only market with a price cap, risk-averse investors prefer a capacity mechanism over scarcity pricing.

Paying for capacity in an electricity market is essentially entering into a forward contract for the use of electricity in the future and can also be used to hedge future price risk. More generally, to understand the relationship between risk and investor behavior in electricity markets, we turn to the foundational literature on how forward contracts affect electricity market outcomes. In a seminal paper, Allaz and Vila (1993) demonstrated with a simple two-stage Cournot duopolist model that forward contracts reduce power producers' sensitivity to spot market prices, which enhances competitiveness of the spot market.[1] If power producers are risk averse, Allaz (1992) found that they will further increase their forward contract position and spot market production, due to a risk-hedging component in their strategic bid. Both Powell (1993) and Green (1999) found that if electricity buyers are risk averse, they may even pay a price premium for forward contracts, due to their effect of lowering spot market prices. Confirming theoretical expectations, Wolak (2000) examined power producers' actual electricity bidding and price-setting processes in Australia's National Electricity Market, finding that risk-averse power producers took on larger forward contract positions and bid more aggressively into the spot market, reducing spot market prices.

Due to the varying details of capacity payments and remuneration for each ISO/RTO, developing an empirical approach to examine the impact of increasing levels of VREs on capacity prices or payments will likely need to vary by market to reflect pertinent structural details. Second, data availability for capacity payments in ISOs/RTOs without formal capacity markets may be limited due to the contractual nature of these payments. To address these limitations, our recommended empirical approach (introduced in the next section) focuses on the underlying drivers for capacity payments. Because capacity payment mechanisms exist to address the missing money in electricity markets that occurs when prices do not adequately reflect the value of investment in resources, we first focus on the impact of increasing levels of VRE capacity on long-term energy prices.

2.2.4.2 Recommended Modeling Approach for Estimating VRE Impacts on Capacity Prices

Our recommended modeling approach builds on Bushnell and Novan (2018), who examined long-term effects of increasing levels of VRE capacity on wholesale market prices in CAISO. Because Bushnell and Novan (2018) relied on capacity-driven changes in renewable output as identifying variation, they did not control for long-run trends in capacity through month-by-year fixed effects, first-differencing, or including lagged prices. Instead, to address the potential for spurious correlation between renewable output and wholesale prices, they controlled for demand and supply factors that could influence both renewable output and prices. To control for demand and weather-related price effects, they included hourly CAISO demand. To control for supply-side effects, they included the Henry Hub natural gas price, as well as precipitation to control for potential hydroelectric output-induced price effects. They also controlled for daily and seasonal fluctuations in demand that can cause wholesale price variation (e.g., renewable output can be correlated with seasonal output from conventional generation and demand, and daily weather can drive variation in renewable output and demand).

[1] The intuition behind this result is that if one power producer can trade forward in a sequential market setting, it does, and obtains a Stackelberg leader position. However, if both power producers can trade forward, they do, and it gives rise to a prisoner's dilemma, making both power producers worse off; but also reducing spot prices below what they would be without a forward contract market. Over many repeated periods, the competitive outcome is achieved.

Our recommended modeling approach differs from that of Bushnell and Novan (2018) in some important ways. We recommend expanding the analysis to a panel of data covering multiple ISOs in more recent time periods. Using a panel of data would allow for the inclusion of ISO-level fixed effects to account for observable and unobservable differences across ISOs, which can improve our ability to control for unobserved confounders. Our recommended approach modifies the model in equation (1) (which was used to estimate short-term price impacts, in Section 2.2.1.2) by removing most of the fixed effects that control for long-run confounding trends. We instead recommend including controls for supply-related shifts that could affect prices. In addition to controls for natural gas prices, which control for shifts in conventional generation, we also recommend including a variable to control for hydropower production. Because hydropower generation could potentially respond to VRE power production, hydropower production could be endogenous. Following Bushnell and Novan (2018), we recommend including monthly precipitation from the National Oceanic and Atmospheric Administration to proxy for hydropower production potential. We also recommend controlling for supply-related shifts due to nuclear capacity. If nuclear capacity changes over the analysis period in any of the ISOs, it should be included in the model. Nuclear generation tends to be a baseload fuel and is unlikely to be correlated with VRE production. Additionally, following Bushnell and Novan (2018), we recommend including monthly fixed effects to control for seasonal shifts in production. All other controls remain the same as in the short-term model.

$$P_{h,d,i} = \alpha_{m,i} + \beta^s Solar_{d,i} + \beta^w Wind_{d,i} + \beta^g NG_d + \theta \boldsymbol{X}_{h,d,i} + \varepsilon_{h,d,i} \tag{7}$$

Where h indexes hour of day, d indexes day, m indexes month of the year, and i indexes ISO. P is the average hourly real-time market price ($/MWh) in each ISO. $Solar$ and $Wind$ are aggregate daily levels of ISO solar and wind (GWh). NG is the Henry Hub natural gas price to control for supply-related shifts from conventional generation that may be correlated with renewable production. X includes hourly ISO load a proxy for hydropower production and, potentially, nuclear generation at each ISO to control for potential supply-related shifts in hydropower or nuclear power capacity. Monthly fixed effects control for season shifts in supply. Errors are clustered at the ISO level. The coefficients of interest are $\beta^s$and β^w, which represent average changes in the ISO real-time market price during hour h caused by a 1 GW increase in solar or wind generation.

In future research, we also recommend examining how VREs impact capacity market prices specifically. Capacity markets tend to secure capacity to meet demand a few years in advance of when the capacity is needed. Examining the impact of increasing levels of VRE capacity on capacity market prices would require controlling for both supply and demand factors other than VRE capacity bid into the market that could influence the price of capacity. Other questions of interest for future research include if the ELCC approach to valuing VRE capacity contributions is superior to the historical performance approach. This question could be answered by examining capacity prices and resource adequacy during scarcity situations before and after ELCC implementation.

An additional question for future research is to empirically investigate how capacity markets affect price volatility, and ultimately risk.

3.0 Revenue Sufficiency

3.1 Background and Relevant Trends

Electricity market revenues are sufficient when payments for energy, capacity, and flexibility cover the fixed and variable costs of providing those services. VREs can decrease average wholesale electricity prices through the merit-order effect. VREs can also increase price volatility with increasing frequency of negative prices. However, VRE intermittency can also lead to the need for more flexible resources. For example, when solar power tapers off for the day, it creates short and steep ramps that need to be met by power producers that can turn on and turn up quickly. But for those power producers to be available in the market, they need to earn sufficient revenue to cover both their fixed and variable costs. If these flexible power producers do not earn sufficient revenue to cover their fixed and variable costs, this revenue insufficiency can lead to a lack of adequate capacity and flexibility in electricity markets (Frew et al. 2016).

Regardless of the current operating conditions, electricity supply must meet electricity demand every second of the day (within accepted tolerance levels to safely and reliably operate the electricity grid). To accomplish this delicate balancing act, market operators must have sufficient electricity supply available to meet the highest level of electricity demand. Under price pressure from VREs, expensive peaking generators—which may be infrequently required to meet peak demand—may not earn enough to stay in the market even though they are needed for reliability (Frew et al. 2016; NERC 2022). If payments from energy, capacity, and flexibility services are not sufficient (i.e., revenues are not sufficient), generators necessary for reliability may exit the market (Frew et al. 2016; Zhou et al. 2021).

In electricity markets, net revenue is a measure of the total revenue received by power producers for energy, capacity, and flexibility services, less the variable costs of producing power. Net revenue measures the amount of money available to cover a power producer’s fixed costs. The gold line in Figure 17 shows the net revenue necessary for a hypothetical natural gas combined cycle unit to cover its fixed costs (estimated levelized fixed cost target) compared to the actual revenues that resource would have received in CAISO by year from 2016 to 2020. Net revenues have not been sufficient to cover fixed costs for several years across several geographic market zones (CAISO 2022b).

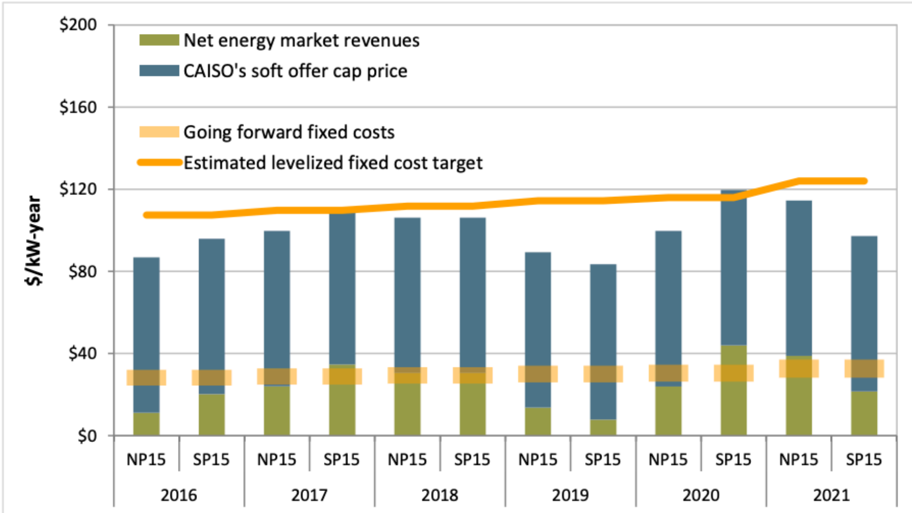

Figure 17. CAISO Net Revenues for Hypothetical Natural Gas Combined Cycle Unit 2016–2021 Source: CAISO 2022a.

However, in today's electricity markets, revenue insufficiency is not limited to just those markets with high levels of VREs. As shown in Figure 18, PJM, a market with far fewer VREs, also had revenue insufficiency for a hypothetical natural gas combined cycles unit across several geographic market zones in recent years (Monitoring Analytics 2021). Parsing out the extent to which VREs contribute to revenue insufficiency—as opposed to other factors such as lower natural gas prices—is an area that needs to be understood to properly address the challenges of VREs on revenue sufficiency.

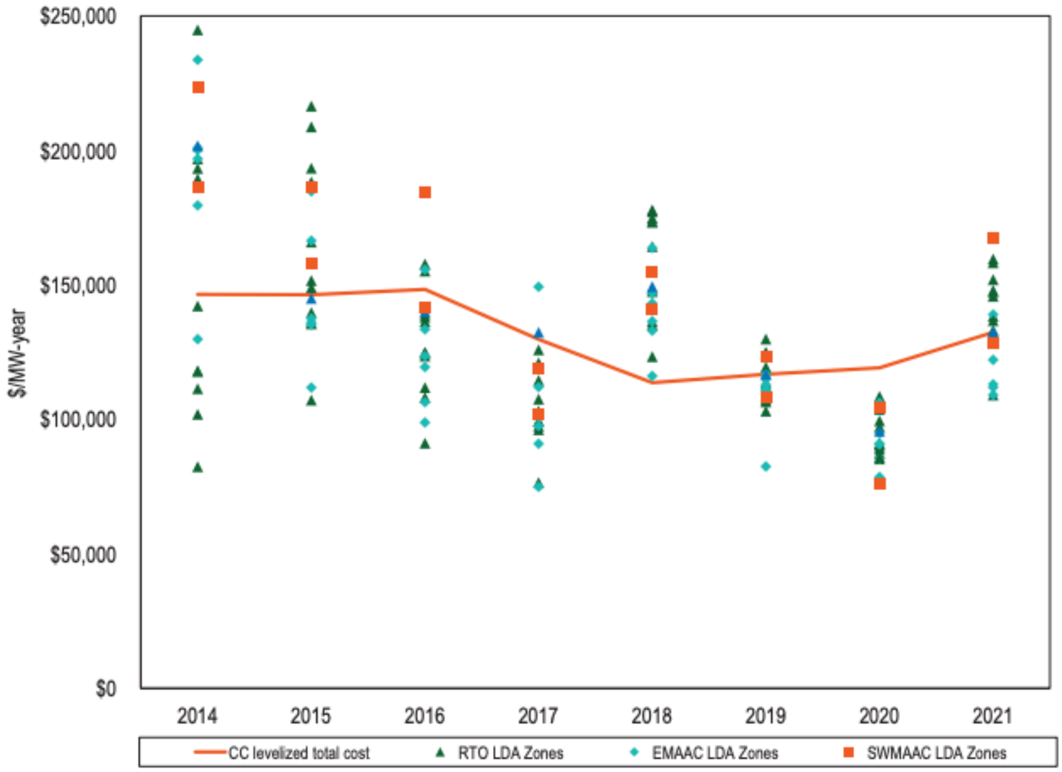

Figure 18. PJM Net Revenues for a Hypothetical Natural Gas Combined Cycle Unit. Source: PJM.

In the related economic literature, most studies on the impact of VREs on revenue sufficiency in electricity markets focus only on the impact of VREs on energy revenues. However, in well-functioning electricity markets, low energy prices could signal adequate capacity. On the other hand, low energy prices could fail to represent the long-run scarcity value of electricity and undermine both resource adequacy and investment incentives for new generation or maintenance of existing generation (Bielen et al. 2017). Because of the nuanced implications of low energy prices, the locational marginal price alone may not be a sufficient indicator of investment needs—especially as expanding renewables deployment increases price volatility—instead, total cost to serve load should be considered (Grubb and Drummond 2018). To address this concern, Section 3.2 provided a comprehensive evaluation of the impact of VREs on revenue streams from energy, flexibility, and capacity markets, as well as other long-term contract mechanisms to identify how VREs affect revenue sufficiency in electricity markets.

3.2 VRE Impacts on Revenue Sufficiency

A recurring theme in the literature on how renewables affect electricity market price formation processes is that through both decreasing revenues and displacing more expensive resources through the merit-order effect, renewables make it more difficult for all resources to recover their fixed costs. Short-term and long-term energy market prices are all affected by VREs. The total revenues a resource receives from wholesale energy and ancillary service markets, as well as long-term payments for capacity through capacity payments or other mechanisms, including PPAs, determine a resource's ability to cover its fixed and variable operating costs—and if it will continue to participate in an electricity market. In this section, we conduct a case study to examine the impacts of VREs on revenue sufficiency. Because of the varied structures of electricity markets across the United States that impact how generators are remunerated, this section begins with an overview of electricity generator ownership models, generator owners, and compensation types. We then provide an overview of our methodology to assess changes to revenue sufficiency from a changing resource mix. We apply our methodology to a detailed case study on the revenue sufficiency of a California utility and discuss questions for future research.

3.2.1 Electricity Generator Ownership Models

In the United States, the markets and underlying policies regulating electricity sales vary considerably. As a result, electricity generators are often owned by a vertically integrated utility in regulated states, and independent power producers (IPPs) in deregulated states. For regulated entities, revenue sufficiency may be less likely of an issue, as they typically receive a guaranteed rate of return on owned assets. IPPs, on the other hand, are compensated through electricity markets or through PPAs. Utility conglomerates often have both regulated generators and IPPs as subsidiaries and operate in both regulated and deregulated markets.

While these different corporate structures help inform the ways that generators are remunerated, compensation types also vary considerably by technology (Figure 19). Renewables are both much more likely to be owned by an IPP and to be contracted under a power purchase agreement. This is likely due to the non-dispatchable nature of the technology and geography. As an example, both California and Texas, which operate under restructured markets (or partially restructured, in the case of California), have large populations and excellent renewable resources. On the other hand, thermal plants are more likely to be owned by vertically integrated electric utilities and are frequently rate-based or used for bidding into competitive markets.

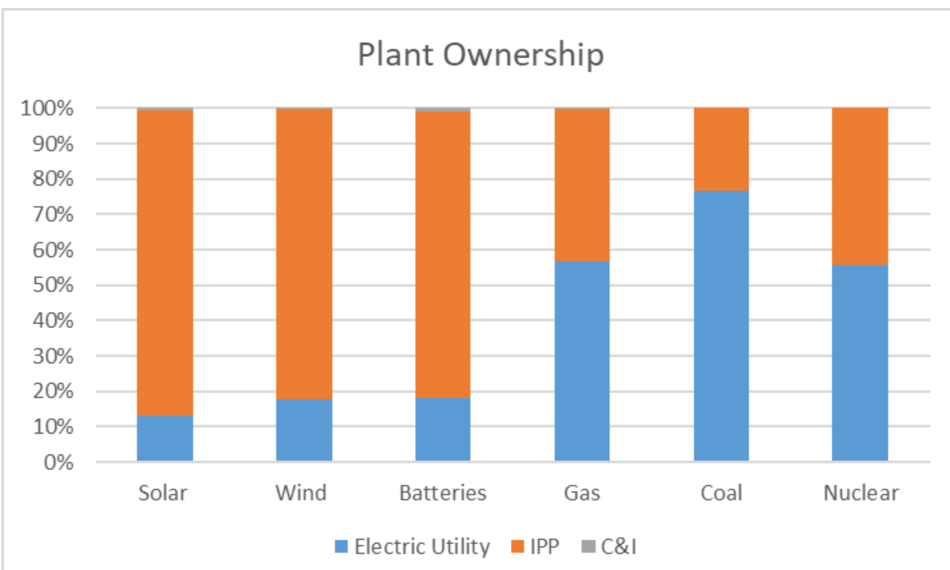

Figure 19. Generator Owners and Compensation Types. Source: EIA-860.

These ownership models have a significant impact on corporate revenues. Rate-based projects offer a rate of return on investment and can generally ensure a plant is profitable over its useful life. Likewise, projects with a PPA have stable revenues and, if priced correctly, ensure an adequate return. Merchant projects do not see these stable revenues and are subject to market conditions. As a result, these projects are subject to greater risk. They may have an outsized impact on revenue as electricity markets evolve.

3.2.2 Methods for Understanding Changing Need for Revenue Sufficiency

Many metrics are used to evaluate the health of either a company or an industrial sector, including revenues, growth, share prices and profit margins. Utilities, especially, are expected to provide a steady rate of return for investors, providing stable and consistent dividends (Boyer and Ciccone 2009). However, the changes in generator remuneration may complicate this arrangement. We propose a method for examining changes to revenue for utilities using data from corporate filings, EIA data, FERC data, and PPA data collected by Lawrence Berkeley National Laboratory. Pairing these sources of data together will allow us to form an annual picture of revenue stemming from generators.

Information found both in corporate annual reports to the U.S. Securities and Exchange Commission and EIA Form-860 allows us to determine ownership in energy generating projects. After categorizing projects by ownership share, we pair this information with data from EIA-923 and FERC's Electronic Quarterly Reports (EQR) to understand the generation profile for these plants. For plants with a PPA, generation is compared with PPA prices to understand annual revenue, while merchant revenue is derived to profits listed in corporate filings and, where necessary, FERC's EQR reports. The remaining revenue from rated based power plants is derived from corporate filings and integrated resource plans. From this analysis, we can see revenue changes in response to a changing resource mix and the influence of remuneration methods on revenue sufficiency for specific companies. This analysis is conducted for one company below but could be replicated for other major utilities.

3.2.3 Case Study – Evolving Revenue Streams in a Major IOU

3.2.3.1 Company Overview

As previous sections have included VRE impacts to CAISO's short-term energy markets, with the selection of this case study, we also focus on changes to the CAISO market, choosing one Sempra Energy (parent company of SDG&E) as our case study. SDG&E is the smallest of the three California investor owned utilities (IOUs) and has had smaller electricity revenue impacts from legal settlements than the state's other IOUs, PG&E and SCE.[1] Sempra has a few business lines and corporate subsidiaries. The largest are SDG&E (a primarily retail gas and electricity provider), Oncor (a transmission and distribution utility in Texas), and Southern California Gas (primarily a retail gas provider). The company also maintained an IPP, Sempra Renewables, until 2018 when the company was dissolved and its assets sold. This transaction was part of a broader trend in the electricity industry, triggered by investor preferences. Some large infrastructure investors prefer to invest in these business lines independently (as opposed to investing through a larger conglomerate) leading to a heightened level of mergers and acquisitions during this period (Walton 2018).

The company also maintains significant investments abroad, with liquified natural gas, generating, and retail sales assets in Central and South America. Though relevant to the company's bottom line, we by and large exclude earnings from outside the United States for this

[1] Sempra did have wildfire and gas leak related settlements in 2017 and 2021 respectively, leading to lower margins and profits in those years (Figure 21)

analysis, as they do not pertain to revenue sufficiency in U.S. electricity markets. That being said, many utilities operate internationally as a strategy to grow revenue, diversify their asset base, and hedge against risk within specific geographies or markets.

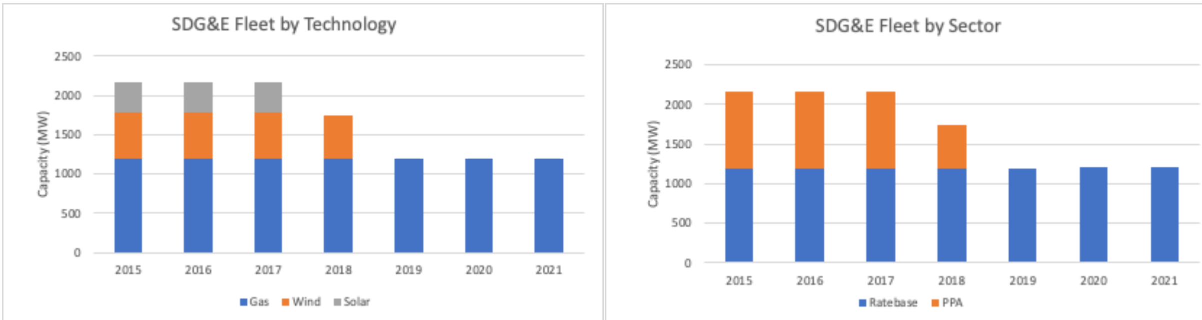

Figure 20. Sempra Fleet Characteristics

In terms of the corporate fleet, Sempra's generators are dominated by natural gas plants, though they owned a not insignificant portfolio of solar and wind generators (Figure 20). The renewables were sold through PPAs (as is typical for solar and wind projects) and the gas generating plants are being remunerated through the SDG&E rate-base. Though many generators bid into the CAISO market, the three IOUs maintain about 6.5 GW of rate-based capacity (primarily nuclear and natural gas) (CPUC 2022b). While this is a significant volume of capacity, it is small relative to the size of the state, which had nearly 82 GW of net summer capacity in 2021 (EIA 2022b).

3.2.3.2 Revenue Streams

SDG&E is a relatively large utility in terms of revenue, averaging about $10 billion in earnings between 2015 and 2021 (Figure 21). Its revenues have grown steadily over this period, while profits have been more inconsistent. Gas and its retail/vertically integrated electricity businesses both account for about half of total profits and revenues, with generation forming a much smaller portion of both profits and revenue. Large drops in electric (2017) and gas (2021) profits were the result of legal settlements. While electricity revenue has increased fairly steadily (a 25% increase between 2015 and 2021), gas revenue growth has been more dramatic (a 58% increase over the same period). Despite this, profit growth (excluding years when the company paid large legal settlements) was more subdued, with growth rates of 20–30%. This may indicate that to date revenues have been sufficient, with higher prices (primarily for gas) being passed through to customers rather than unfairly burdening either party.[1]

[1] California utilities are allowed to pass through the costs of purchased power and fuel directly to customers, and do not earn a rate of return on these purchases (CPUC 2022b).

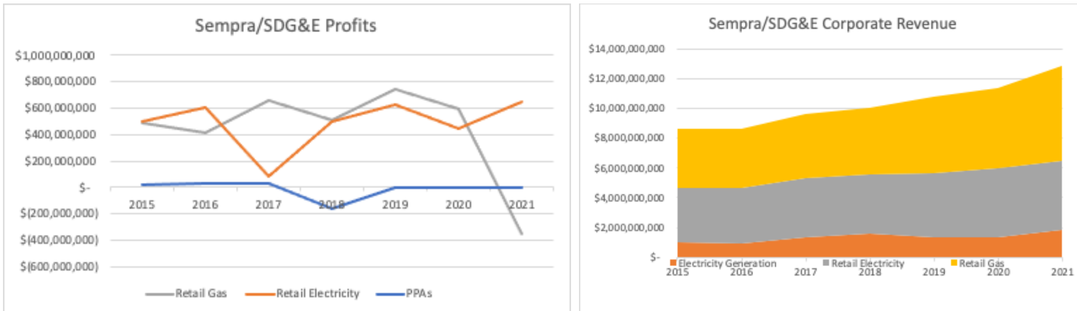

Figure 21. Sempra Profits and Revenues over Time

A more complicated picture emerges when we examine revenues and profits of the company's wind and solar projects (Figure 22). Solar projects show both stable earnings and profits, highlighting some of the benefits of PPAs. Annual profits are generally quite high for solar considering the competitiveness of the PPA market. SDG&E records average profit margins of nearly 40%, while equity returns for operating utility PV projects are generally assumed to be closer to 10% (Feldman et al. 2020). This may be because the projects date to the earlier years of the solar PV industry when deals were inked at very high prices (over $100/MWh in some cases). Competition may have brought down returns since these were built.

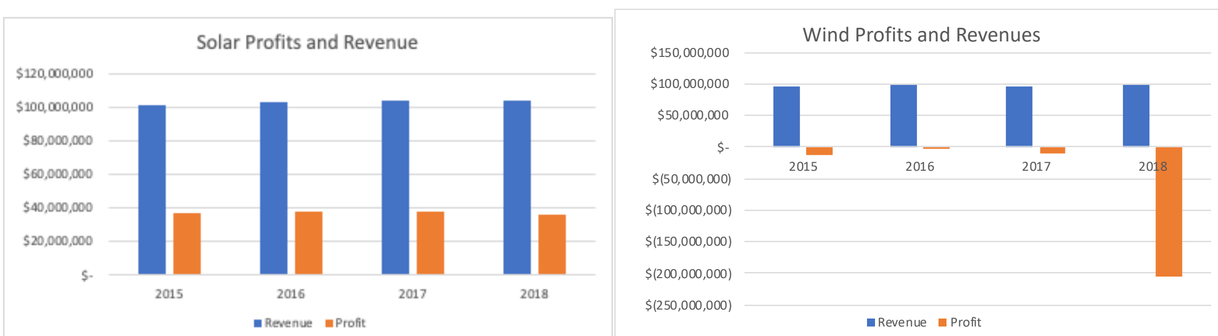

Figure 22. Profits and Revenues from Solar and Wind PPAs

Sempra's wind projects, on the other hand, do not break even in most years, though they report large impairment charges in some years (particularly 2018) stemming from the anticipated sale of the projects. This disguises some of the actual costs associated with these projects. Tellingly, these wind projects signed much lower PPAs than the company's solar projects but included escalation rates (which many of the solar projects did not), so it is likely that Sempra intended to recoup many of these losses through earnings later in the PPA period.[1]

[1] PPA contracts are typically structured as buy-all sell-all agreements between the electricity purchaser and project operator. That is, the purchaser will agree to buy all (or in conjunction with other purchasers, a percentage) of the project's output at a given price. As an example, a utility could agree to purchase 50% of a project's output at $50/MWh. Many, though not all, of these contracts include annual escalators, allowing the purchase price to increase at a predefined rate over time.

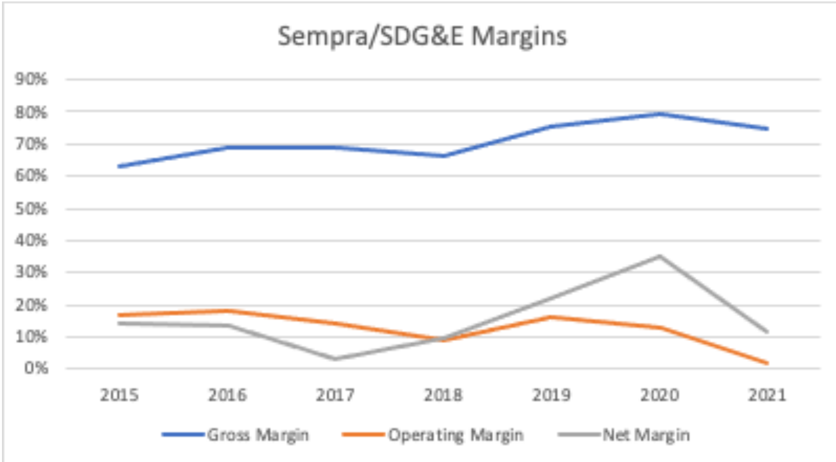

Figure 23. Corporate Margins

Finally, despite changes to their business models, legal settlements, the sale and acquisition of companies, and the exit of their renewable PPA business, Sempra's margins have been remarkably stable (Figure 23), ranging from about 65–78% for gross margins and 5–35% for net margins. Gross margins are high, as utilities generally have low costs of sales (operating costs and investment costs are proportionally higher). Large drops in net margin occurred in response to legal settlements, but the company otherwise did not see large spikes in profitability.

3.2.3.3 Discussion

Despite massive changes to the California energy market, Sempra has been relatively stable financially as a company. However, this in and of itself does not fully answer the questions of revenue sufficiency in a zero marginal cost electricity market. Sempra has substantial revenue stemming from its regulated gas and electricity holdings, which could be cushioning some of the financial risk. While rate-basing could help protect corporate earnings, it may result in higher costs for customers and less efficient outcomes (Cicala 2022). This would be less than ideal. However, when we examine renewables specifically, a more complicated picture emerges. Some of Sempra's plants were extremely profitable, while others operated at a loss. Some of this may be attributable to timing and others to corporate strategy.

Answering some of these more pertinent questions will require broader investigation. Analysis of merchant plants would show how disruption to electricity markets is impacting merchant generators. Likewise, a broader analysis of renewable projects could filter out any corporate strategy or market timing impacts. A broader geographic scope could also provide some lessons learned. For example, capacity markets could have an impact on revenues in a way that is only clear if they are compared to generation only markets. Evaluating broader impacts will be critical, as energy markets and earnings evolve in response to renewables and clean energy goals.

4.0 Market Power Monitoring and Mitigation

4.1 Background and Relevant Trends

The potential for exercising market power in wholesale electricity markets is again due to the unique characteristics of electricity markets—demand is inelastic, electricity cannot easily be stored, and electricity supply is relatively concentrated (e.g., due to network topology, transmission limitations, and inelastic demand, one or few suppliers may be able to raise price above marginal cost, exhibiting market power). These characteristics create opportunities for power producers to exercise market power when there are short-term supply and demand imbalances. Addressing market power in electricity markets is particularly difficult, as market power can either be vertical, where a single firm is vertically integrated, owning production and transmission, or horizontal, where a single firm controls a significant share of capacity in the market. In related electricity market literature, several studies have pointed to outcomes consistent with producers exercising market power even in restructured markets (Borenstein et al. 1999; Chen and Hobbs 2005; Puller 2007; Sweeting 2007; Hortaçsu and Puller 2008; Bushnell et al. 2008).[1]

Market power has been partially addressed in electricity markets through pricing rules (such as price caps) that limit the ability of producers to exercise market power but, as discussed in previous sections, these pricing rules also distort price signals. For example, price caps may prevent scarcity or shortage prices from reaching the levels needed to incentivize investment, creating a missing money problem (Joskow and Tirole 2007; Milstein and Tishler 2019). The missing money problem is only a part of the issue. Price caps can also contribute to the reliability issues on the demand side. In theory, price caps reduce electricity retailers' incentives to purchase power through long-term contracts (and hedge price risk) when the most they are willing to pay for electricity in the short-term market is the price cap (Wolak 2021). However, as seen in Texas in February 2021, even high price caps may not be sufficient to ensure a market solution to reliability, and other public policy interventions may be necessary. Because of the relationship between price caps and reliability, how market power is monitored and mitigated is a key consideration for how increasing levels of VREs impact market power, as price caps are one of the main tools for mitigating market power in electricity markets.

To add to the challenge, increasing amounts of VREs create short, steep ramps that temporarily increase the need for flexible resources. As these flexible resources could potentially exercise market power in situations where they are one of few resources available to meet supply and demand imbalances, monitoring and mitigating market power may become more difficult. As

[1] All of the referenced studies provide evidence that historical electricity prices are more closely predicted by models that assume strategic behavior from participants rather than perfect competition. Borenstein et al. (1999) provide a survey of the literature and discuss characteristics of electricity markets which create opportunities for exercising market power that remain relevant today; Chen and Hobbs (2005) find that simulated prices in PJM using a Cournot model with a forward market approximated actual PJM prices, except in peak demand periods; Puller (2007) finds that historical prices in California could be best predicted by simulating strategic producer behavior with a Cournot model; Sweeting (2007) found firms exercised considerable market power in England and Wales, based on analyzing actual prices compared to prices predicted by a Cournot model; Hortacsu and Puller (2008) use a supply function equilibria (SFE) approach in Texas to examine the market after restructuring, and find that firms with large market shares behave as strategic oligopolists; Bushnell et all. (2008) find that in organized electricity markets throughout the United States, historical electrical prices are closely predicted by a Cournot model with a forward commitment.

evidence of this concern, Browne et al. (2015) found that returns to peaking resources increased significantly under high amounts of VREs. Further, with high amounts of VREs, competitive offers depend on the opportunity costs of operating resources (e.g., storage technologies), which increases the difficulty of monitoring markets for market power (Zhou et al. 2021).

4.2 Empirical Evaluation of VREs on Market Power

Monitoring market power under the increasing penetration of VREs is challenging, as VREs cause short and steep ramps that need to be met by flexible resources, creating opportunities for those resources to exercise market power. Further, Somani and Tesfatsion (2008) point out that it is difficult to construct measures that reliably detect market power in electricity markets. However, the ability of resources to exercise market power also depends on the rules that govern the market, such as price caps that limit the exercise of market power. The existing structure of the market also defines the potential for resources to behave strategically and exercise market power. These market rules and structures need to be considered when parsing out the impact of increasing amounts of VREs on the exercise of market power. Although the focus of this review is on the ex-post impacts of VREs, in this section, we also review ex ante simulation literature to glean important insights for VREs and market power.

In an early examination of the potential impact of large amounts of VREs on market power in Great Britain, Green and Vasilokos (2010) used expected wind projection and demand data for 2020 to implement a supply function equilibria model. They found that in the presence of significant market power (assuming two firms owned all the remaining fossil-fuel capacity), market prices would more than double, while volatility of those prices would increase. However, average revenues of wind plants would rise by 20% less than baseload plants. Similarly, Twomey and Neuhoff (2010) examined the impact of increasing levels of wind power on market power in the Netherlands under different assumptions about the degree of market competitiveness (perfectly competitive, monopoly, and Cournot). They found that although wind resources decrease average market prices, conventional generators can raise market prices when little wind power is being produced. Forward contract markets reduce, but do not eliminate, this effect. Further, VREs benefit less from the exercise of market power than conventional resources. Mountain (2013) provided empirical evidence in support of Twomey and Neuhoff (2010) from the impact of wind on the South Australian Electricity Market.

VREs also affect congestion in power markets, which could create opportunities for exercising market power. Using an agent-based modeling framework, Guerci and Sapio (2012) determined that although wholesale prices in Italy are lower due to the merit-order effect, conventional generators can exercise market power due to increased congestion from renewable resources. Bigerna et al. (2016) found similar impacts due to transmission congestion in Italy in more recent work. Because renewable energy resources increase transmission line congestion, they disentangled market power from transmission congestion rent by constructing a residual demand curve that considers transmission constraints. They then assessed market power by computing a zonal Lerner index (ZLI) that analyzes the correlation of market power, congestion, and renewable energy supply. They found that exercise of market power has considerably weakened during traditional peak hours due to renewable energy supply but has been reinforced in off-peak hours when markets split due to zonal congestion. Their findings point to flexible natural gas generators exhibiting market power during congested hours.

Short run increases in wind power production reduce spot market prices due to the merit-order effect, which is well documented in the literature, but long-run effects are less clear as increased wind power capacity also changes new investment in other types of resources. Browne et al. (2015) examined long-run impacts of increasing renewable energy on market power using a capacity expansion model to simulate new capacity investment, with an agent-based simulation model to find the (strategic) prices of the new resource mix. They found that exercising market power depends on individual firms' ratio of capacity to peak demand. The intuition of this finding is that when reserve margins are narrow, it is optimal to build more peaking units, resulting in higher market prices. As wind capacity increases, average prices decrease, but the opportunity to exercise market power increases in some periods, with returns to peaker generators increasing significantly in the shoulder hours.

Looking to the future, Ekholm and Virasjoki (2020) examined market power under a hypothetical 100% VRE system. In this system, price formation is determined by demand and storage charging/discharging decisions rather than traditional merit-order supply costs. Although energy storage and elastic demand resolve temporal supply and demand imbalances, they find that market power can be exerted by both curtailing VRE and, to a lesser extent, by intertemporal storage decisions. However, they also point out that regulators could readily observe strategic curtailment decisions made by VREs.

How increasing levels of VREs, energy storage, and more elastic demand affect market power in electricity markets is another important area for future research.

5.0 Impact of Incentives, Economic Trends, and Market Design

5.1 Background and Relevant Trends

Price formation and grid operational concerns due to VREs are driven by both climate regulation and economic incentives that reduce the cost and risk of these VRE capacity additions (Lee 2021). For example, in the United States, energy tax credits to promote non-fossil-fuel resources have been available since 1978, with a marked increase in these tax credit expenditures for solar resources in recent years (Sherlock 2021). Many states also have clean energy or renewable portfolio standards (RPSs) that encourage the production of power from VREs. Figure 24 shows clean energy and renewable standards by state as of 2020.

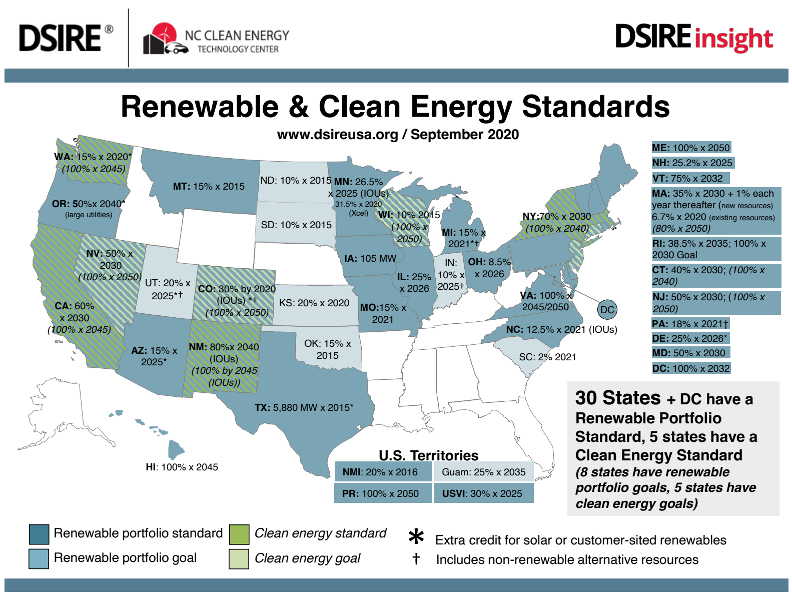

Figure 24. Clean Energy and Renewables Portfolio Standards. Source: DSIRE.

Although the effectiveness of RPSs in driving increasing amounts of VREs is up for debate—Upton and Snyder (2017) found little difference in renewable generation between states with and without RPSs—what is clear is that they provide other avenues for revenue, allowing VREs to be profitable even under negative energy prices. Further, increasing amounts of VREs have come online in recent years, concurrent with the availability of these various federal and state subsidies. Figure 25 shows U.S. electricity generation by major source, with a clear increase in VREs occurring in the last decade as a share of total generation.

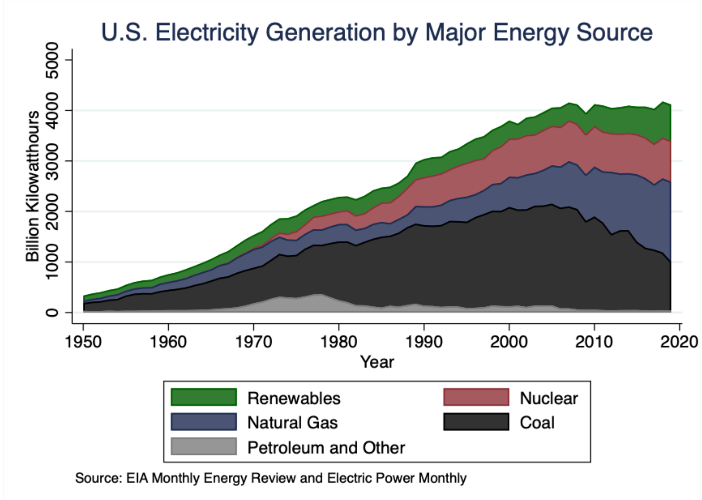

Figure 25. U.S. Generation by Source. Source: EIA.

Additionally, VRE costs have decreased significantly. Lazard (2021) estimates unsubsidized levelized cost of energy (LCOE) for wind and solar each year. Figure 26 shows the LCOE for wind and solar from 2009 to 2021. The LCOE estimates for wind and solar have decreased by 72% and 90% from 2009 to 2021, respectively. When considering U.S. federal tax subsidies, the LCOE estimates have decreased by 77% for wind and 87% for solar from 2009 to 2021.

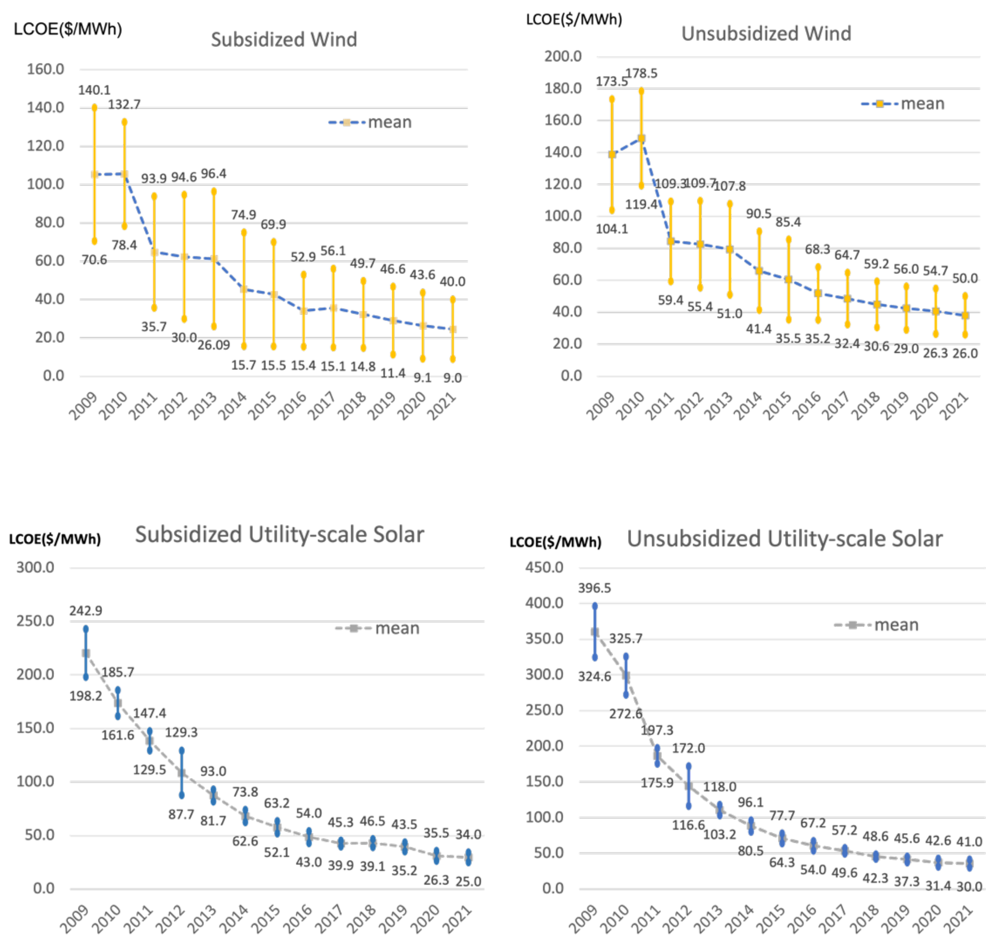

Figure 26. Subsidized and Unsubsidized Levelized Cost (in 2020 dollars) of Energy for Wind and Solar. Source: Lazard 2021.

As a case in point, over the past two decades California has enacted regulations that encourage electricity production from VREs and reduce greenhouse gas emissions.[1] These regulations have caused significant changes to the resource mix in California (e.g., from 2011 to 2020, California solar power production increased from 0.11% to 14.2% of total in-state generation).[2]

But increasing amounts of VREs are not the only change that has occurred in the last two decades that significantly affect the electricity grid portfolio of resources, grid operations, and electricity prices. Post-2008, improvements in hydraulic fracturing techniques led to sustained decreases in natural gas prices and substantial natural gas generation (Joskow 2013). This decrease in natural gas prices, paired with increasing amounts of VREs, has also led to a remarkable decline in coal generation (Fell and Kaffine 2018).

[1] In 2002, California passed regulations to subsidize VREs, and in 2006 California passed the Global Warming Solutions Act.
[2] Data on California electrical energy generation available from the California Energy Commission at: https://www.energy.ca.gov/data-reports/energy-almanac/california-electricity-data/california-electrical-energy-generation (accessed 1/26/2022).

As an example, Figure 27 plots the capacity factors of coal and natural gas combined cycle plants since 2011, indicating coal plants are also being used less while natural gas plants are being used more.

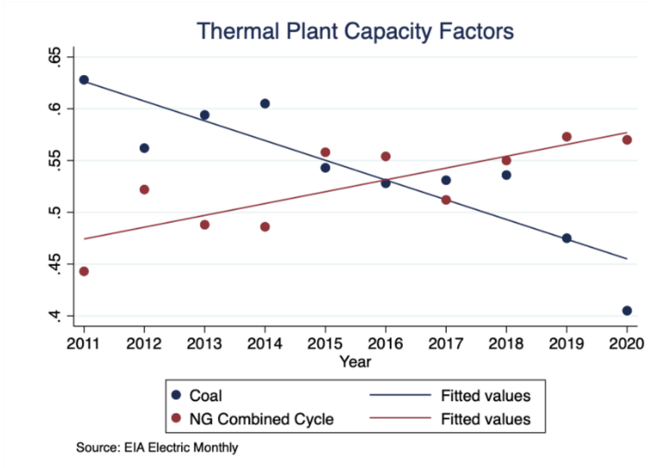

Figure 27. Thermal Plant Capacity Factors

The impact of increasing amounts of VREs on coal plant retirement is less clear cut, due to other factors such as SO_2 emissions enforcement, planning reserve margins, variations in load growth, and age of plants influencing retirement decisions (Mills et al. 2017).

Figure 28 shows trends in natural gas prices (in million dollars per British thermal unit) compared to coal capacity retirements (in megawatts) by year. In the post-2008 period there is a marked increase in coal plant retirement with a sustained decrease in natural gas prices.

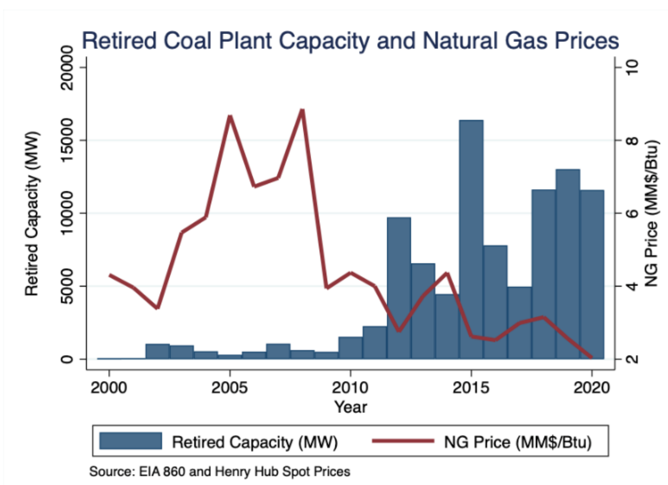

Figure 28. Coal Plant Retirements and Natural Gas Prices

Additional changes to market design, such as expanding the footprints of existing markets to better balance VREs, are underway. For example, as discussed in Section 2.1.1, CAISO's EIM market, launched in 2014 with PacifiCorp, has since extended membership to vertically integrated, rate-regulated balancing authorities across the West, as shown in Figure 29. With membership to the market, CAISO has offered enhanced grid reliability and improved integration of VREs due to increased visibility of trades and CAISO's sophisticated dispatch algorithm.

Figure 29. Western Energy Imbalance Market 2021. Source: CAISO.

Looking forward, as renewables are expected to continue to grow as a relative share of the generation mix,[1] grid challenges can be expected to continue, with new market designs and operational responses required to balance the effects of VRE intermittency. However, because changes in the last decade have been driven by several factors, including increasing renewables, state- and federal- policy incentives that promote renewables or demote carbon-intensive plants, and declining natural gas prices, the effects of these various drivers need to be disentangled to understand the true impact of increasing amounts of VREs on the grid.

5.2 Empirical Evaluation of VRE Impacts from State-Level Incentives and Market Design

In this section, we examine the empirical literature to understand how important policy and regime changes influence increasing levels of VREs, as well as how VREs impact climate-related policy goals. We also discuss how market design can impact the successful integration of VREs.

5.2.1 State-Level Incentives

Various federal- and state-level policies encourage additional VRE investment. Although there is a building consensus in the literature that, due to the diminishing marginal revenue for additional VRE investments, policy incentives that encourage additional VRE capacity investments are in turn encouraging investment in resources that may have little market value (Wiser et al. 2017; Bushnell and Novan 2018), renewables portfolio standards remain a leading policy incentive for decreasing greenhouse gas emissions across the United States. While Upton and Snyder

[1] Based on data from EIA's short term energy outlook, available at https://www.eia.gov/outlooks/steo/report/electricity.php#:~:text=We%20expect%20the%20share%20of,in%20the%20electric%20power%20sector (accessed 1/28/2022).

(2017) did not find significant differences in renewable generation across states with and without RPS legislation, Greenstone and Nath (2020) found that RPSs lower emissions by 10–25%, while raising prices by 11%, seven years after their passage.[1] RPS programs have played a significant role in U.S. climate policy, and states continue to adopt goals for future emissions reductions through clean energy standards (CESs).

Figure 30 provides a visual overview of the difference in renewable resource requirements among states' RPSs or CESs; darker green states are those with more stringent RPSs or CESs. Beyond the renewable or clean energy requirement (e.g., electricity supply from 100% of clean energy by a target year), some states also target specific technologies or disincentivize fossil-fuel technologies. For example, in Washington State, the Washington Clean Energy Transformation Act requires coal plants within Washington to be eliminated by December 31, 2025 (if not eliminated, the electric utility or affected market customer must pay an administrative penalty of $0.150/kWh); retail sales of electricity to Washington electric customers must be greenhouse gas neutral by January 1, 2030 (alternative compliance payments of $0.150/kWh for coal based, $0.084/kWh for natural gas based peaking power plants, and $0.060/kWh for natural gas combined cycle must be paid for each MWh of electricity used to meet load that is not electricity from a renewable resource or non-emitting electricity generation); there is no new hydro allowed except under tight restrictions; and, by January 1, 2045, 100% of all sales of electricity to Washington retail electric customers must be from non-emitting or renewable resources (SB 5116).

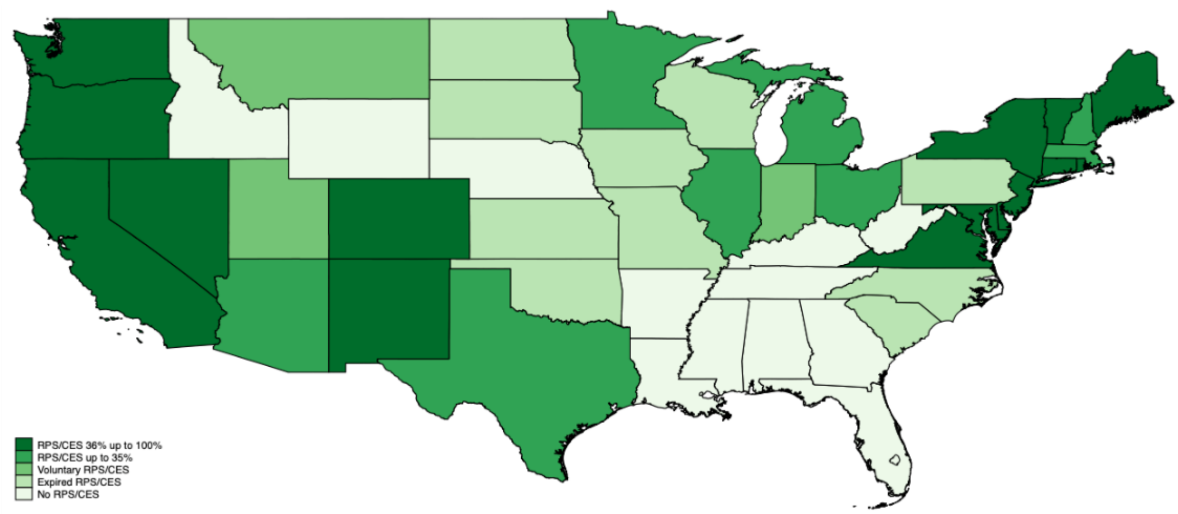

Figure 30. RPS and CES Stringency. Source: Author's Depiction Based on Data from DSIRE and the National Conference of State Legislatures.

To examine the empirical implications of climate-related policies, most studies use econometric techniques, such as difference-in-differences or synthetic control, to compare electricity prices in states that adopt an RPS or CES to those that did not adopt such standards before and after the implementation of the policy. There are a few key challenges for determining the effects of an RPS or CES, including controlling for endogeneity in policy adoption (if states that adopt an RPS select into that policy based on factors that affect future electricity prices, this will bias results) and the potential for RPS policy effects to spill over into other states, controlling for the

[1] Greenstone and Nath (2020) also point out that most RPSs also overstate their effect on net generation by grandfathering in existing renewable generation into statutory requirements.

effects of confounding climate policies, as well as addressing the potential for states to experience different effects from the RPS policy over time, which can bias results.

Although research on the effect of RPS or CES on energy prices has been performed in the aggregate for average effects across states, less research has focused on the differential effects of different types of policies or regime changes in specific states. In future work, VRE-inducing policy changes at the individual state level can be assessed using the synthetic control method. The synthetic control method addresses potential endogeneity in policy adoption by matching a particular state of interest (e.g., Washington) to a synthetic state (synthetic Washington), which is a weighted average constructed from other states with similar characteristics, where characteristics are chosen to account for those variables that both influence electricity prices and the adoption of VRE-inducing climate policies.

5.2.2 Emissions Impacts

The ultimate goal of climate-related policies and regime changes that encourage investment in VREs is to reduce greenhouse gas emissions through displacing emissions-intensive conventional generators. An important implication of these policies is to understand how well they work at reducing emissions. Actual emissions offsets depend on the type of generator that is on the margin, reducing its output in response to VRE generators. In the literature, a common empirical approach is to regress emissions variables against stochastic wind or solar generation, controlling for load and other confounding factors.

Cullen (2013) examined the impact of wind generation on emissions in Texas, finding that, on average, wind generation reduced more emissions from gas generators than coal generators. Kaffine et al. (2013) examined the impact of wind generation on marginal emissions offsets in Texas, finding that increasing levels of wind generation resulted in a reduced emissions rate that varied over the course of the day. Novan (2015) also examined the effect of increased levels of wind generation in Texas, but did so with an instrumental variables approach—instrumenting for wind power production with wind speed and direction—to account for the effect of wind curtailment. His findings were largely the same as Kaffine et al. (2013), who instead regressed emissions on stochastic wind generation (and did not account for curtailment), while controlling for demand and other confounding factors. Callaway et al. (2018) extended the temporal and spatial impact of VREs on marginal emissions reductions to their effect on investment incentives. They used variation in fossil-fuel production across days with similar demand profiles to predict a marginal emissions rate. They then applied that rate to simulated wind data to estimate investment costs for renewable resources under different wind and solar patterns. They found that emissions benefits vary significantly across regions, but not technologies. Further emissions reductions benefits make up a significant portion of the return on VRE investments.

A potential model to determine the short-term impact of wind or solar on emissions offsets is

$$E_{t,i,j} = \alpha_t + \beta^s Solar_{t,i} + \beta^w Wind_{t,i} + \beta^g NG_t + \boldsymbol{\theta X_{t,i,j}} + \epsilon_{t,i,j} \tag{8}$$

Where t is the time index representing hour of day (h), day of month (d), or month of year (m). The ISO of the observation is indexed by i. $E_{t,i,j}$ is the average hourly CO_2 emissions for generator j, in ISO, i. $Solar_{t,i}$ and $Wind_{t,i}$ are hourly levels of ISO solar and wind (GWh). NG_t is the monthly Henry Hub natural gas price to control for supply-related shifts from conventional generation that may be correlated with renewable production. $X_{t,i,j}$ includes hourly ISO load to control for emissions-effects due to demand levels. Hourly correlation between wind or solar output and demand that varies throughout the day is accounted for with hour-of-day fixed effects. Differences in generator emissions due to seasonality are controlled for with generator-specific month and day-of-week fixed effects. Errors may need to be corrected for potential cross-sectional or serial correlation.

5.2.3 Market Design Impacts

Market designs are changing to accommodate the operational challenges of increasing amounts of renewable resources. An example is the Western EIM (EIM) introduced by CAISO to the Western electric region. The EIM extends a centralized, real-time market over a traditionally rate-regulated region. The EIM's main benefits are that it improves economic dispatch by allowing CAISO to find the most economic generators in the combined EIM area, it creates diversification benefits from improving integration of renewable resources, and it improves grid reliability from increased transparency of transmission and generating assets across the Western electric region (Hogan 2017).

Tarufelli and Gilbert (2021) examined how the EIM changed dispatch patterns and emissions outcomes across the Western electric region from 2010 to 2019 and found that there are significantly different effects on coal and gas generators. EIM market participation caused gas generators outside of California to increase power production and emissions during the evening ramp and night hours, when wind is a larger share of the generation mix. However, EIM participation caused coal generators to systematically ramp down in response to peak solar generation from California, reducing coal emissions. The change in dispatch patterns and emissions outcomes depend on the generation mix dispatched to meet renewable energy imbalances.

As market designs continue to evolve to better integrate renewable resources, changes to the effective resource mix will be important in determining its climate impacts. However, as we transition to a zero marginal cost future with increasing amounts of clean energy resources, emissions impacts may become less of a concern. New challenges in price formation, revenue sufficiency, reliability, and market power mitigation are emerging for the zero marginal cost future.

6.0 Distributed Energy Resources: Demand Response and Energy Storage

While VREs increase the variability of net load that needs to be met by dispatchable resources, other levers available to address this variability include DERs such as demand response and energy storage. Although most of these resources remain limited in their deployment due to barriers to adoption, economics, and other reasons (as will be discussed in the ensuing section), a review of existing trends and recent literature provides some themes for understanding how greater deployments of these resources could impact price formation processes in the future.

6.1 Demand Response

By making customers more responsive to prices, demand response better aligns customers willingness to pay for electricity with their actual consumption and incentivizes customers to shift or change their consumption in response to price signals, reducing peak demand and lowering the need for both power and transmission capacity (DOE 2006). Specific to price formation processes, Hurley et al. (2013) highlighted that demand response can reduce price volatility, improve the price-elasticity (price-responsiveness) of demand, and reduce energy prices for all customers. Figure 31 demonstrates that by reducing demand, demand response can reduce energy prices for all market participants. By reducing peak demand, demand response also limits generators' ability to exercise market power (Zarnikau and Hallett 2008).

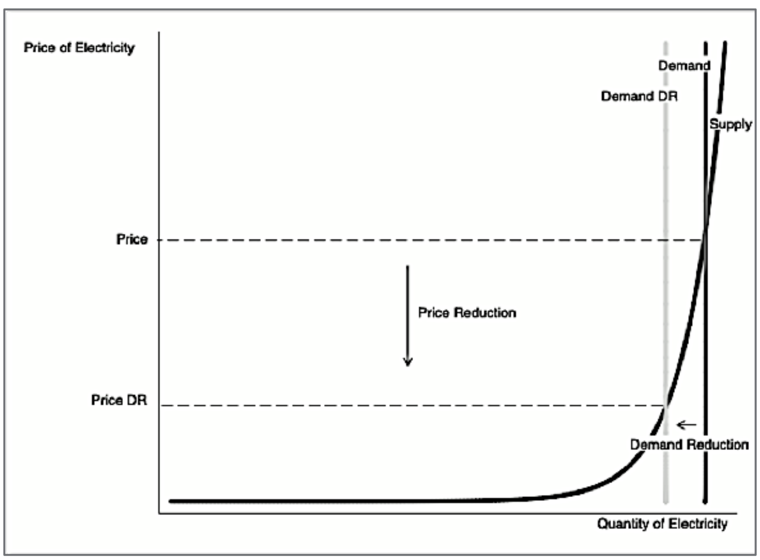

Figure 31. Price-Reducing Effects of Demand Response. Source: Reproduced from Tarufelli (2020) based on DOE (2006).

Demand response participation typically falls under two categories: (1) incentive-based programs that reduce customer demand during peak or critical demand periods by paying customers for demand reductions, or (2) price-based programs that reduce customer demand during high price periods by allowing customer rates to reflect real-time electricity costs (DOE 2006; Chen and Liu 2017). Both types of participation have their challenges. In incentive-based programs customers are typically paid for a reduction in demand from their baseline or typical demand, thus establishing the baseline is critically important. In price-based programs, customers need enabling technology, such as real-time metering, that allows customers to respond to market price signals. In addition, in price-based programs, a tradeoff between giving customers advanced notice of prices (as with time-of-use pricing), which reduces demand sensitivity, or exposing customers to real-time prices, which increases demand sensitivity (but also exposes customers to more price volatility), must be made. Cappers et al. (2012) found that mass market demand response could help integrate VREs but noted a range of barriers to participation for both types of demand response that remain relevant today. For price-based demand response, there is a need for real-time pricing coupled with automation and control technology. For incentive-based pricing programs, customers will need to be willing to participate in programs that feature short duration and frequent demand response events. Because demand response has experienced limited deployment due to barriers to participation as well as lack of access to enabling technology, empirical evidence of the effect of demand response on price formation processes tends to focus on results from pilot programs, barriers to participation, and opportunities for future deployment of demand response resources.

Price-based demand response programs include both static and dynamic pricing programs where static programs include time-of-use rates that set prices for certain hours and days, and dynamic programs include both real-time pricing and critical-peak pricing, which allow prices to change on much shorter notice. Empirical research on price-based demand response programs tends to focus on pilot programs, which is how real-time or other dynamic pricing programs are currently implemented in the United States. Faruqui and Sergici (2010) performed a survey of 15 dynamic pricing programs in the United States, finding that ownership of central air-conditioning, the magnitude of the price increase, and enabling technologies (such as smart thermostats) were crucial for peak load reductions. In a meta-analysis of time-varying rate programs (mostly time-of-use) from 63 pilot programs, Faruqui et al. (2017) found that customers reduce peak loads in response to higher peak to off-peak price ratios, and peak load reductions are stronger when customers are provided with enabling technology. Echoing this finding, in a recent review of 83 demand response pilots and programs, Parrish et al. (2019) found that automation technologies increased reported price responses by 15%. However, Parrish et al. (2019) also pointed out that most pilots are static peak pricing or load control (discussed next), but more research is needed on more dynamic forms of demand response.

Incentive-based programs can be either classical or market based (DOE 2006). Classical programs include direct load control and interruptible or curtailable load programs, whereas market-based programs include emergency demand response, demand bidding, ancillary service, or capacity market programs in the wholesale markets (DOE 2006). Parrish et al. (2019) surveyed nearly 52 demand response pilots and programs, of which 10 studies were on direct load control programs, and found that demand reductions from the baseline varied widely, ranging from 0% to nearly 80%, with variation in response driven by access to automation technology, the size of a customers' baseline demand (customers with higher heating or air conditioning loads tended to have larger reductions), and whether the program was opt-in or opt-out.

In their assessment of demand response participation, FERC (2021) found that although overall demand response participation (in the wholesale markets) decreased by 4% from 2019 to 2020, the percent of peak demand that could be met by demand response increased from 6% to 6.6% due to lower peak loads. Further, Parrish et al. (2019) pointed out that customer participation in existing demand response programs and pilots is often limited to less than 10% of the target population. To improve participation in demand response programs, several barriers to participation must be addressed.

As advanced metering infrastructure roll outs are underway across many regions of the United States, there is potential that an important barrier—access to enabling technology—may soon be overcome. However, O'Connell et al. (2014) found that establishing reliable control strategies and market frameworks to encourage participation remain key challenges for demand response. Reliable control strategies are necessary so that efficient communication can occur across a complex, diverse, and geographically distributed system. Market frameworks typically limit participation to emergency support and ancillary services (limiting participation in the day-ahead market) and require strict performance and telemetry standards (O'Connell et al. 2014). Dupuy and Linville (2019) documented several barriers that impede participation of demand response resources in wholesale markets, including complex market rules for participation, aggregation requirements that restrict participation by resource location and size, and requirements that resources be available 365 days per year, which may be infeasible for some types of demand response, including air conditioning loads. See Tarufelli et al. (2022) for an overview of current participation rules. However, the ongoing implementation of FERC Order 2222, which allows participation from third-party aggregators, will likely impact how demand response resources participate in the wholesale electricity markets; see Eldridge and Somani (2022).

Other important barriers to participation relate to customer behavior and rate design. Customers' risk perception, knowledge of enabling technologies, and exposure to actual energy prices (as opposed to other fixed charges) can all affect demand response participation and remain important areas for future research (O'Connell et al. 2014; Brown and Chapman 2021).

Most studies that evaluate how demand response can help integrate VREs utilize ex-ante modeling approaches that assess the potential for flexible load to enable VRE integration in power systems; see Jordehi (2019) for a recent review of the literature. Some key themes are that demand response should reduce system peak and moderate variability in demand, reducing both system costs and VRE curtailment (De Jonghe et al. 2012; McPherson and Stoll 2020). However, Parrish et al. (2019) point out that most modelling approaches overestimate the amount of demand response that will likely be achieved in electricity markets, highlighting that incorporating more realistic demand response details in modeling approaches is an important area for future research. Another important limitation in analysis of demand response programs and their interaction with increasing levels of VREs is that most empirical research is on a program-by-program basis, primarily due to data availability. As demand response increases across electricity markets, and data on demand response impacts becomes more widely available, studying the impact of demand response and its interaction with VREs at more aggregate levels is an important area for future research.

6.2 Energy Storage

Energy storage is another technology that has the ability to mitigate price formation impacts from VREs by price-arbitrage, charging when energy prices are low and sending power to the grid when prices are high, effectively balancing periods of over- and under-supply from VREs (O'Connell et al. 2014). However, energy storage remains limited in its deployment due to high costs of energy storage, although these costs are decreasing, as shown in Figure 32 (Wood Mackenzie 2021).

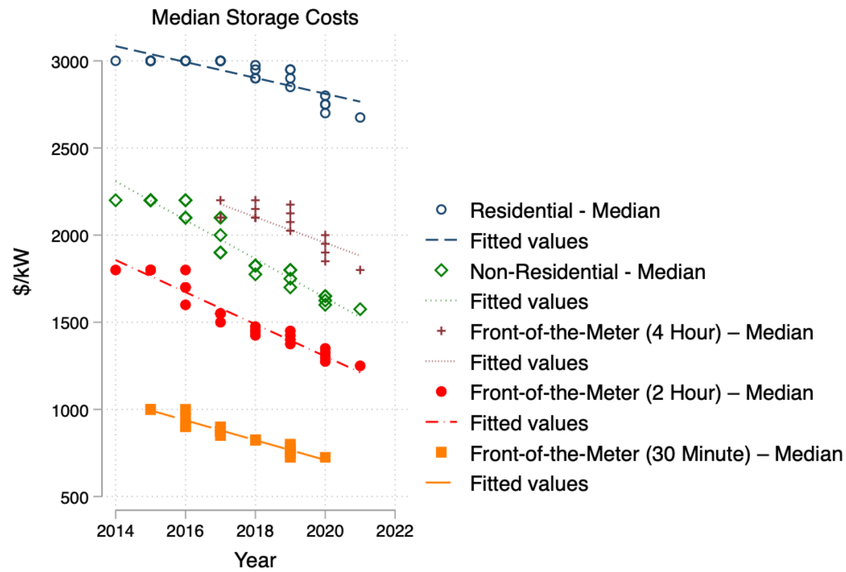

Figure 32. Median Storage Costs for Energy Storage Systems. Reproduced from Boff et al., 2022 with data from historical Energy Storage System Price Trends through Q1, 2021. Source: Wood Mackenzie 2021.

Energy storage is comprised of a variety of technologies, each appropriate for different applications (Ibrahim et al. 2008; Tan et al. 2021). In reviews of the literature, both Akinyele and Rayudu (2014) and Tan et al. (2021) highlighted that energy storage has been shown to stabilize renewable output (Gabash and Li 2012; Lund et al. 2015); provide ancillary services such as reserves, power quality, and reliability (Gayme and Topcu 2012; Chong et al. 2016); reduce peak load; save overall system generation costs; and defer capacity investments (Gayme and Topcu 2012; Poudineh and Jamasb 2014). However, the findings in the literature primarily focus on the role of battery storage within models of the electricity grid and optimal control strategies rather than an empirical evaluation of actual battery performance.

With respect to how energy storage can impact price formation and revenue sufficiency, a major focus is on energy arbitrage, or the ability of an energy storage system to store energy when prices are low or negative, and discharge when prices are high. However, the potential for price-arbitrage depends on a variety of factors, including costs of generation for baseload and peak generators, penetration and coincident peak of VREs, availability of flexible resources, and daily demand profiles (Staffell and Rustomji 2016). Further, in a study of how different energy trading strategies would affect the value of arbitrage for pumped-storage hydropower and compressed air energy storage across four markets in Europe, Zafirakis et al. (2016) found that as markets integrate and become more efficient, the value of arbitrage was reduced, and thus additional revenues would be needed to support the cost of energy storage systems. That additional revenues would be needed to cover the investment costs of energy storage systems is a common finding in the literature (Staffell and Rustomji 2016). More recent literature considers stacked benefits (e.g., co-optimizing benefits from both energy and ancillary services) (Hittinger and Ciez 2020).

One of the main limitations of wide-scale deployment of energy storage is due to the high costs of energy storage systems (Spataru 2022), although costs are rapidly decreasing (Hittinger and Ciez 2020). Policy changes, such as the energy storage mandate enacted by California in 2013, are causing further decreases in storage costs, enabling economies of scale and learning by doing. Through difference-in-differences, synthetic control, and learning curve analyses, Boff et al. (2022) found that the cost reductions in energy storage systems costs attributed to California's storage mandate are as much as $1,630 for a 1 MWh battery.[1]

Other important limitations for widescale deployment of energy storage systems include the technological maturity of some systems, as there is a need to increase the capacity and efficiency of energy storage systems, as well as market and regulatory barriers that impede increased market penetration of storage technologies (Spataru 2022).

Some important areas for future research in energy storage systems are to develop more standardized and generally applicable storage models (Hittinger and Ciez 2020), as well as to understand the actual (rather than expected) impacts of energy storage on price formation and other important services with empirical analysis as energy storage deployment increases in electricity markets.

6.3 Looking to the Future

Traditionally demand response focused on incentive-based programs that were adopted based on the predictable nature of electricity demand, but the introduction of increasing levels of VREs will require more flexible and continuous demand response (O'Connell et al. 2014). Chen and Liu (2017) highlight that transactive energy is a variant and generalized form of demand response, as it can align consumer behaviors with the needs of the entire system, maintaining a dynamic balance of supply and demand. Several recent transactive energy demonstrations and simulations have shown that transactive energy can be used to incorporate VREs and manage DERs to flatten load and reduce operational constraints, demonstrating an important option for the future management of the distribution grid (Hammerstrom et al. 2008, 2009; Widergren et al. 2014a, 2014b; Samad and Bienert 2020; Reeve et al. 2022).

[1] These cost savings are only related to battery cells, non-battery costs can account for as much as 60% of total costs, so this is likely a conservative estimate of cost reductions induced by the mandate (Boff et al. 2022).

7.0 Conclusions and Next Steps

With this in-depth analysis of electricity markets and literature review, we have identified several key challenges to electricity market design and operation from increasing levels of zero marginal cost resources, including their impacts on price formation, revenue sufficiency, reliability, market power monitoring and mitigation, and how state-level incentives and market design impact VREs and these challenges. Last, we consider how DERs, including demand response and energy storage technologies may help integrate and moderate the challenges of VREs.

Key takeaways are that VREs displace more expensive, emissions-intensive generators in electricity dispatch, which reduces emissions but also causes short-term energy prices, on average, to decline. Short-term energy price impacts due to VREs vary temporally, geographically, and by the underlying resource portfolio. The variability in price impacts can also affect market power monitoring and mitigation. However, examining VRE's impact on short-term energy price impacts alone is insufficient, as low energy prices could signal adequate capacity or inadequate investment incentives for generators necessary to keep electricity supply reliable. Obtaining a complete picture of revenue sufficiency requires examining VRE impacts to all potential revenue streams, including short-term energy prices, ancillary service prices, capacity and other long-term energy prices (including PPAs), and price volatility.

In ancillary service markets, we find mixed results. Some research has found that VREs reduce both short-term energy prices and ancillary service prices, as these markets are typically linked. However, other research finds that VREs increase demand (and prices) for ancillary services. In capacity markets, research has found that increasing the capacity of VREs also decreases long-term energy prices on average, but because the effect varies temporally (decreasing price in some periods while increasing prices in others, depending on VRE availability), increasing levels of VREs may undermine economic incentives for some conventional resources to stay in the market.

Because PPA data has limited availability, we performed a case study on Sempra Energy, the parent company of SDG&E, to examine how revenues from VRE PPAs, as well as other short- and long-term revenue sources, affect overall revenue sufficiency. We found that while some renewables plants have been extremely profitable, likely due to the prevailing high prices at which the PPAs were signed, others have operated at a loss.

Increasing levels of VREs may be driven by state- and federal-level incentives and climate-related policies. We found that state-level renewable policies tend to increase short-term energy prices but have mixed results on emissions. However, we also identify the need for more in-depth research on a state-by-state basis, as policies have significant heterogeneity in their enactment and implementation.

Last, we find that although demand response and energy storage deployment remain limited due to barriers to adoption, economics, and other reasons, these technologies are expected to stabilize VRE output and reduce curtailment, reduce demand variability, reduce system peak load and save system costs, as well as contribute important ancillary services.

Throughout our analysis, we have highlighted important questions for future research, especially in the less-studied areas of VRE impacts on ancillary services, capacity, and PPA prices. To conduct this research, we have recommended several empirical models which, when estimated, will contribute to the literature on understanding how VRE impacts market design and operation.

Questions for future research:

- Short-term energy price impacts
  - We recommend a model for determining the short-term impact of wind or solar generation on spot market prices in equation (1). We recommend the model be estimated in three ways: (1) as a pooled regression across all ISOs and hours to understand how VREs impact average real-time market price across all ISOs, (2) as a separate regression for each hour of the day to examine how VREs impact real-time market prices over time, and (3) by ISO to understand how VREs impact real-time market prices over space.
  - We recommend that additional analyses be performed to examine the robustness of results to the impact of outliers in individual ISOs (e.g., the sensitivity of results to transmission congestion, generator outages, out-of-market actions, and extreme weather events). Future work could also expand our recommended modeling approach to a more granular level within ISOs, examining nodal price impacts, to understand the local impacts of VREs.
  - We identify that the impact of VREs on retail prices is an important area for future research.
- Volatility impacts
  - We recommend a modeling approach that utilizes some combination of an MS-GARCH type model, as shown in equation (5)—that has the ability to capture both regime changes and asymmetries that are important volatility determinants—be adopted to model volatility in electricity prices
- Ancillary service impacts
  - We recommend a modeling approach for estimating VRE price impacts on ancillary services that recognizes important drivers in the demand for and supply of ancillary services, including load variability, potential generator outages, wind or solar forecast errors, expectations of energy market prices (opportunity costs), and fuel costs. Our recommended model is shown in equation (6).
  - We also recommend a seemingly unrelated regression approach be applied to the short-term energy price impact equation (1) and the AS equation (6) for co-optimized energy and ancillary services markets.
- Capacity price impacts
  - We recommend a modeling approach that identifies the effects of increasing levels of VRE capacity on wholesale market prices, as shown in equation (7).
  - We also identify questions for future research, including examining how VREs impact capacity market prices, examining if the ELCC approach to valuing VRE capacity contributions is superior to the historical performance approach, and examining how capacity markets affect price volatility and, ultimately, risk.
- Revenue sufficiency impacts
  - We recommend expanding our case study methodology to a broader set of firms and markets to understand how energy markets and earnings are evolving in response to renewables and clean energy goals.
- Market power monitoring and mitigation

  - We identify how VREs, energy storage, and more elastic demand affect market power in electricity markets and that this is an important area for future research.
- Impact of incentives, economic trends, and market design
  - We recommend the impacts of state-level policies that encourage adoption of VREs or other changes to the resource mix be examined in more detail, potentially using the synthetic control method.
  - We recommend a model to determine the short-term impact of VREs on emissions offsets in equation (8).
- Distributed energy resources: demand response and energy storage
  - We recommend an in-depth examination of barriers to demand response deployment and how they can be addressed.
  - We recommend development of modeling approaches with realistic amounts of demand response integration.
  - We recommend that as demand response increases across electricity markets, and data on demand response impacts becomes more widely available, studying the impact of demand response and its interaction with VREs at more aggregate levels.
  - We recommend an in-depth examination of barriers to energy storage deployment and how they can be addressed.
  - We recommend development of more standardized and generally applicable storage models.
  - We recommend studying the actual impact of energy storage and its interaction with VREs at more aggregate levels on price formation and other important services as energy storage deployment increases in electricity markets and data becomes more widely available.

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Appendix A – Volatility Price Impacts

A.1 Volatility Price Impacts

A.1.1 ARCH/GARCH

ARCH stands for autoregressive conditional heteroskedasticity. The name of the ARCH model implies that the model works with time-varying variances (i.e., heteroskedasticity) that depend on lagged effects (i.e., autocorrelation). The popularity of this model stems from its variance specifications, which can capture commonly observed features of the time series of financial variables. It is useful for modeling **volatility** and especially *changes in volatility* over time.

However, some of the weaknesses are that it often requires many parameters and a high order of the ARCH term to capture the dynamic behavior of conditional variance; this tends to overpredict the volatility since it responds slowly to isolated shocks in returns, and it fails to capture the leverage effect (Schmidt 2021).

GARCH stands for generalized autoregressive conditional heteroskedasticity (Bollerslev 1986). The difference between ARCH and GARCH stems from the inclusion of a moving average along with the autoregressive component. The GARCH model allows for a more flexible lag structure by imposing nonlinear restrictions that enable reduction in the number of parameters in the model, thus addressing one of the limitations of ARCH. More simply, GARCH is the autoregressive moving average (ARMA) equivalent of ARCH.[1]

Both ARCH and GARCH fail to capture the asymmetric relationship between asset returns and volatility changes.

Nelson's (1991) EGARCH model has been shown to overcome the weaknesses of the symmetric models—in particular, the leverage effect.

Variants of both ARCH and GARCH models have been used in the context of forecasting electricity prices, even in the context of renewables. For a more detailed mathematical formulation of the ARCH and GARCH models, please refer to Greene (2007) (chapter 21) and Hamilton (1994) (Chapter 21).

Table A.1. Example Applications of ARCH-GARCH Models

Authors	Title	Model
Hua et al. 2005	Electricity Price Forecasting based on GARCH model in Deregulated Market	GARCH
Garcia et al. 2005	A GARCH Forecasting Model to Predict Day-Ahead Electricity Prices	GARCH
Hickey et al. 2012	Forecasting hourly electricity prices using ARMAX–GARCH models: An application to MISO hubs	ARMAX-GARCH

[1] https://web-static.stern.nyu.edu/rengle/GARCH101.PDF

Authors	Title	Model
Wang et al. 2022	Forecasting renewable energy stock volatility using short and long-term Markov switching GARCH-MIDAS models: Either, neither or both?	Markov switching GARCH-MIDAS
Shen and Ritter 2016	Forecasting volatility of wind power production	Markov Regime Switching-GARCH

A.1.2 ARIMA/ARIMAX/SARIMAX

ARIMA is a class of models that explains a given time series based on its own past values (i.e., its own lags and the lagged forecast errors) so that the equation can be used to forecast future values. If the time series is non-seasonal, then a simple ARIMA model can be used. If, however, there are seasonal patterns in the time series, then a seasonal ARIMA (SARIMA) model needs to be deployed.

Within the ARIMA class of models, there is another subset—the auto-ARIMA—that combines auto regression, differencing, and a moving average into a single model.

ARIMAX is similar to ARIMA, however it also considers independent variables create more exact forecasts. Auto-ARIMAX is similar to auto-ARIMA in that it combines autoregression and moving average to provide reliable forecasts after calculating the optimal values for certain parameters automatically and differencing the historical data to make it stationary if the need arises. However, auto-ARIMAX also considers *independent variables* (e.g., temperature or gross domestic product) that can explain various changes in the time series and help in creating more exact forecasts. This method of forecasting is suitable when the enterprise wishes to forecast data that is stationary/nonstationary, and multivariate with any type of data pattern (i.e., level/trend /seasonality/cyclicity).

If the auto-ARIMA also has a seasonal component to it, then it is a SARIMAX.[1]

While ARIMA models are quite capable at modeling the overall trend of a series along with its seasonal patterns, they do not perform quite as well when dealing with outliers/extremes (i.e., values that fall outside the norm). For a more rigorous mathematical formulation of ARIMA and its extensions, please refer to Greene (2007) (chapters 19-22) and Hamilton (1994) (chapter 3).

[1] https://www.scmconnections.com/get-smart/simple-guide-auto-arima-sarima

Table A.2. Example Applications of ARIMA/SARIMA/SARIMAX Models

Authors	Title	Model
Zhao et al. 2017	Improving short-term electricity price forecasting using day-ahead LMP with ARIMA models	ARIMA
Basmadjian et al. 2021	Day-Ahead Forecasting of the Percentage of Renewables Based on Time Series Statistical Methods	SARIMAX, SARIMA, ARIMAX

A.1.3 Regime Switching Models/Markov Switching Models

The Markov switching model of Hamilton (1989), also known as the Regime Switching Model, is one of the most popular nonlinear time series models in the literature. Traditional time series models assume that one set of model parameters can be used to describe the behavior of the data over all time. This assumption is limiting in the context of real-world data. This is where regime switching models come in. They characterize the data as falling into different recurring "regimes" or "states," thus allowing the characteristics of the time series data (mean, variance and model parameters) to change across regimes with the probability that the series may be in any of the regimes and may transition to a different regime.[1]

More formally, regime switching models are models that allow parameters of the conditional mean and variance to vary according to some finite-valued stochastic process with states or regimes. The regime changes reflect, or aim at capturing, changes in the underlying financial and economic mechanism through the observed time period (Lange and Rahbek 2009).

Though Markov switching models have been used and proven to be useful in a wide range of contexts, like all models, they have some drawbacks. Most importantly, Diebold and Rudebusch (1994) and Kim et al. (2008) assume that the Markov chain determining regimes is completely independent from all other parts of the model, which is extremely unrealistic in many cases. Additionally, the Markov chain that determines the state of the regime in virtually all of the existing switching models is assumed to be strictly stationary and cannot accommodate non-stationarity in the transition probability. This assumption can be restrictive, especially if the transition is strongly persistent (Chang et al. 2017).

For a more rigorous mathematical exposition on Markov switching models, please refer to Greene (2007) (chapter 22) and Hamilton (1994) (chapter 22).

Table A.3. Example Applications of Regime Switching/Markov Switching Models

Authors	Title	Model
Cifter 2013	Forecasting electricity price volatility with the Markov switching GARCH model: Evidence from the Nordic electric power market	Markov switching GARCH

[1] https://www.aptech.com/blog/introduction-to-markov-switching-models/

Wang et al. 2022	Forecasting renewable energy stock volatility using short and long-term Markov switching GARCH-MIDAS models: Either, neither or both?	Markov switching GARCH-MIDAS
Shen and Ritter 2016	Forecasting volatility of wind power production	Markov Regime Switching-GARCH

A.1.4 MIDAS Models

Missed data sampling (MIDAS) models are regressions that involve time series data sampled at different frequencies. A typical time series regression model involves data sampled at the same frequency. The interest in MIDAS regressions addresses a situation often encountered in practice where the relevant information is high frequency data, but the variable of interest is sampled at a lower frequency. Because MIDAS models involve regressors with different sampling frequencies they are not autoregressive models, since autoregression assumes that data are sampled at the same frequency in the past. MIDAS models share some features with distributed lag models but also have unique novel features. More formally, MIDAS models specify conditional expectations as a distributed lag of regressors recorded at some higher sampling frequencies (Ghysels 2004).[1] For a more rigorous mathematical description of MIDAS models, please refer to Armesto et al. (2010).

Table A.4. Example Application of MIDAS Models

Authors	Title	Model
Wang et al. 2022	Forecasting renewable energy stock volatility using short and long-term Markov switching GARCH-MIDAS models: Either, neither or both?	Markov switching GARCH-MIDAS

A.1.5 Bayesian Models

Bayesian models for modeling volatility are simply extensions of all the frequentist models but with a conditional probability aspect tagged on to it. In situations where the parameter space is large, as compared with the available number of observations, Bayesian estimation methods (where priors from literature are employed) outperform the frequentist models. For a more thorough introduction and approach to Bayesian methods and their applicability, please refer to Koop (2003).

[1] https://www.sr-sv.com/nowcasting-with-midas-regressions/

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