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Price responsiveness of solar and wind capacity demands

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Abstract

Accurate estimates of the price responsiveness of residential, commercial, and industrial electricity demands are essential for energy policy modelling, integrated resource planning, and determining a competitive wholesale electricity market's generation levels, prices, and capacity investments. Hence, we estimate the own-price elasticities of solar and wind capacity demands of a load serving entity (LSE) that provides retail electricity service, thereby answering two interrelated research questions: (1) does solar capacity demand far exceed wind capacity demand? and (2) are solar and wind capacity demands price-elastic? Inspired by the theory of input demand under input price uncertainty, our innovative methodology integrates (a) wholesale spot energy price forecasts by time of day; (b) pseudo data found by minimizing a LSE's annual risk-adjusted budget for procuring solar and wind capacities; and (c) econometric analysis of (b) to estimate the extent of substitutability between solar and wind capacities and the own-price elasticities of solar and wind capacity demands. Using Texas as an illustrative example, we find that when solar and wind power purchase agreements have similar energy prices, solar capacity demand is approximately four times wind capacity demand. Further, the own-price elasticity estimates are -5.34 for solar capacity demand and -5.65 for wind capacity demand. As a result, solar and wind capacity demands tend to substantially grow (shrink) in response to declining (rising) solar and wind energy prices. This lends support to proposals to raise solar and wind energy prices for mitigating the adverse effects of large-scale variable renewable energy development on an electric grid's efficient operation and system reliability. However, adopting such proposals also slows the grid's pace of decarbonization, thus underscoring the policy and regulatory challenges in the quest for a clean and sustainable electricity future. Hence, our policy recommendation of price managing solar and wind capacity demands is a topic of policy debate that deserves the attention of an electric grid's stakeholders.

1. Introduction

This paper estimates the price responsiveness of solar and wind capacity demands of a load serving entity (LSE) that provides retail electricity service in a competitive wholesale electricity market characterized by volatile spot energy prices and large-scale development of variable renewable energy (VRE). Intended for a diverse readership interested in cleaner production, it encompasses multiple interrelated areas, including electricity demand estimation, demand side management, an electric grid's planning, pricing and operation under wholesale market competition, and power purchase agreements (PPAs) in connection to a LSE's VRE procurement under wholesale spot energy price uncertainty. Balancing easy understanding and technical accuracy as instructed by the editor and four diligent reviewers, this admittedly long introduction is a synopsis of the paper that uses methods and materials which may be unfamiliar to some readers of this international transdisciplinary journal.

For concreteness and clarity, the paper uses Texas as an illustrative example to demonstrate its methodology's applicability and real-world relevance. Nevertheless, its formulation and reasoning are transferable to other regions of the world.

1.1 Why does electricity demand's price responsiveness matter?

Electricity demand's price responsiveness is often measured by the own-price elasticity: $E \equiv$ percentage reduction in electricity demand due to a one-percent increase in electricity price (Varian, 1992). As $E \leq 0$, it is considered small when its absolute value $|E|$ is close to zero. Electricity demand is said to be price-elastic when $|E| > 1$.

Accurate own-price elasticity estimates for residential, commercial and industrial demands are essential for such applications as energy policy modelling (Manne et al., 1979), integrated resource planning (Hobbs, 1995), and determining a wholesale electricity market equilibrium's generation levels, prices, and capacity investments in renewable (e.g., hydro, solar and wind) and thermal (e.g., nuclear, coal- and natural-gas-fired) power plants (Milstein

et al., 2024). These applications reflect that electricity generation can only come from power plants already in place. Hence, the short-term market equilibrium is characterized by time-varying generation by an existing fleet of power plants with diverse technologies (e.g., combined cycle gas turbines that burn natural gas and solar plants and windfarms that have zero fuel costs) and time-varying electricity prices that balance hourly market demands and supplies. The long-term market equilibrium is characterized by capacity investments made by independent power producers and renewable energy developers based on their maximization of expected profits.

To underscore the importance of price responsiveness, consider the own-price elasticity estimates of approximately -0.1 found by Woo et al. (2018) for the retail electricity demands of residential, commercial, and industrial customers in the US. These small elasticity estimates discourage an electric grid's independent system operator (ISO) like the Electric Reliability Council of Texas (ERCOT) from heavily relying on wholesale spot energy price changes to manage the grid's aggregate demand, especially when these changes are only partially passed through to retail electricity prices (Brown et al., 2020). They also mean that the ISO should perform market surveillance and sanction the independent power producers found to have manipulated wholesale market prices to achieve profit levels that far exceed those obtainable under unfettered competition (Borenstein et al., 2002).

Motivated by the noted above applications, we estimate the price responsiveness of solar and wind capacity demands attributable to VRE procurement of a LSE, which can be a competitive retailer or a regulated local distribution company (Glachant et al., 2021). If solar and wind capacity demands are very price-elastic, they substantially grow (shrink) in response to declining (rising) energy prices of solar and wind PPAs. In short, large own-price elasticity estimates suggest effective price management of solar and wind capacity demands to shape solar and wind capacity additions. This suggestion is beyond the commonly known

reasons for large scale VRE development, including easy transmission access, aggressive renewable portfolio standards, generous feed-in-tariffs, and various government supports (e.g., low-cost financing and tax credits) (Smirnova et al., 2021), as well as the improvement in cost and output performances of newly built solar plants (Bolinger et al., 2021) and windfarms (Wiser et al., 2021).

1.2 VRE development for deep decarbonization

Reflecting the net-zero target of the United Nations (UN), the United States (US) reaffirmed its commitment to deep decarbonization at the 2021 G20 Summit held in Rome to tackle the urgent threat of climate change (G20 Rome Leaders' Declaration, 2021), necessitating large-scale VRE development to reduce the US carbon-emitting consumption of fossil fuels (Williams et al., 2014). Similar commitments made by other participating countries of the G20 Summit and major CO₂-emitting countries like China and India underscore the global effort to achieve the UN's net zero targets.

Mirroring the US commitment to deep decarbonization is the US Energy Information Administration's Annual Energy Outlook 2023 (DeCarolis and LaRose, 2023, p.12), which projects (a) the total installed generation capacity in the US by 2050 will more than double the 2022 level of ~1,300 GW to meet the nation's rising electricity demand due mainly to economic growth and electrification of vehicles and appliances; (b) nearly 100% of the capacity increase will come from VRE development; and (c) solar capacity addition will be about three times wind capacity addition. In parallel, the International Energy Agency reported in June 2023 that the world's addition of solar capacity in 2024 would be approximately twice the wind capacity addition (International Energy Agency, 2023).

1.3 VRE's procurement and capacity additions

There are two reasons for the nexus between VRE's procurement and capacity additions. First, a competitive wholesale electricity market has inevitably volatile spot energy

prices with occasional spikes (Gal et al., 2017), which can cause a LSE to become financially insolvent (Woo et al., 2003a). Second, AEO 2023 projects rising natural gas prices, which contribute to escalating wholesale electricity prices due to natural gas being the dominant marginal generation fuel in the US (Zarnikau et al., 2023). A major factor in AEO's projection is the increase in the US export of LNG, which helps reduce European dependence on the Russian supply of natural gas (US Energy Information Administration, 2023).

A LSE can mitigate its exposure to wholesale electricity price volatility and spikes by procuring PPAs with fixed forward energy prices (Woo et al., 2004a), including those for VRE (Woo et al., 2023). As a result, the rising procurement of VRE PPAs tells a demand-side story of solar and wind capacity additions, complementing the commonly known reasons listed at the end of Section 1.2.

1.4 Short-term solar and wind capacity additions

Using Texas as an illustrative example, we remark that despite VRE development's cannibalization effect on solar and wind generation investments (Woo et al., 2023), Texas's construction of VRE plants continues unabated. Based on the interconnection agreements already signed between VRE developers and ERCOT, Figure 1 shows that Texas's total installed solar capacity is 14.1 GW in November 2022, which may reach 33.9 GW by December 2024. While Texas's total installed wind capacity is 36.0 GW in November 2022, it may reach 40.6 GW by December 2024. The projected 74.5 (= 33.9 + 40.6) GW of installed VRE capacity by December 2024 is ~50% of Texas's ~145 GW of total installed generation capacity at the end of 2022 (Watson, 2023), underscoring its important role in meeting Texas's peak demand of 83.6 GW recorded on 08/01/2023 (ABC News, 2023).

Solar and wind capacity additions like those portrayed in Figure 1 have adverse effects on an electric grid such as Texas's. Good cases in point include (a) increased requirement for operating reserves (*aka* ancillary services) that equals 5% to 7% of an electric grid's daily

forecast of system peak demand (Zarnikau et al., 2020); (b) exacerbated transmission congestion that impedes the power flow from VRE-rich regions (e.g., sunny deserts and windy coasts) to load-heavy regions (e.g., large cities and industrial zones) (Cao et al., 2022); and (c) diminished investment incentives for dispatchable generation resources like natural-gas-fired power plants and energy storage systems (Hargreaves et al., 2015) that are necessary for maintaining system reliability and resource adequacy (Wolak, 2022). The same can be said about the similarly adverse effects of escalating market penetration of VRE on electric grids in other parts of the world.

Corroborating AEO 2023's long-term projection of VRE plant construction, Texas's short-term projection of solar capacity addition by December 2024 is 19.8 (= 33.9 – 14.1) GW, which is **4.3** times wind capacity addition of 4.6 (= 40.6 – 36.0) GW, thus partially alleviating the concerns of Texas's policymakers and public utility commission in connection to large-scale VRE development's adverse effects on the state's electric grid. This is because solar plants have relatively high daytime output on hot summer days (UL Services Group, 2021) and disperse across ERCOT's renewable regions, unlike windfarms that have relatively high nighttime output and mainly reside in West Texas, where now there are interregional transmission constraints (Woo et al., 2023). As a result, solar generation can, on a per MW basis, better serve a summer-peaking region like Texas with high aggregate electricity demand during hot and sunny afternoon hours. However, abundant behind-the-meter solar generation by rooftop photovoltaic systems during midday hours can cause the California "duck curve" problem, as noted by an insightful reviewer and explained in Appendix 1.

1.5 Research questions

VRE developers have mainly been relying on long-term PPAs of up to 20 years to obtain long-term project financing (Gohdes et al., 2022). However, short-term VRE PPAs of five to seven years are increasingly popular in the US (Roselund, 2019). This sparks our

research questions of (1) does solar capacity demand far exceed wind capacity demand? and (2) are solar and wind capacity demands price-elastic?

Our affirmative answer for (1) reveals that when solar and wind PPAs have similar energy prices, solar capacity demand is approximately four times wind capacity demand. Our affirmative answer for (2) means that solar and wind capacity demands tend to substantially decline in response to rising solar and wind energy prices, thus mitigating the adverse effects of large-scale VRE development on an electric grid like Texas's. However, such capacity demand reductions may not occur when solar and wind energy prices follow their respective declining trends reported by Bolinger et al. (2021) and Wiser et al. (2021).

1.6 Methodology

Motivated by Section 1.5, we propose an innovative methodology to estimate the price responsiveness of a LSE's solar and wind capacity demands. With minor modifications, this methodology is applicable to other parts of the world that have competitive wholesale electricity markets, large-scale renewable energy deployment, and volatile wholesale electricity prices (e.g., other US states like California and those in the Pacific Northwest, Canadian provinces of Alberta and Ontario, European countries like France, Germany, Spain and the United Kingdom, Asia-Pacific countries like Australia and New Zealand, and South American countries like Brazil and Chile).

To demonstrate our methodology's applicability, we first use ERCOT's monthly averages of the real-time hourly energy prices at the system level for the 132-month period of Sep-2012 to Aug-2023 (excluding Feb-2021) to develop spot energy price forecasts by time of day (TOD) for the forward-looking periods of one year, three years, five years, and ten years, where the daytime hours are 07:00 to 19:00 and the nighttime hours are the remaining hours of the day. We exclude Feb-2021 due to the extreme weather event of Winter Storm Uri causing multiday rolling blackouts and wholesale electricity price spikes of up to

\$9,000/MWh (King et al., 2021). Our regression-based approach for developing spot energy price forecasts is equally applicable to the wholesale electricity markets in other parts of the world where natural gas is often the marginal generation fuel (e.g., other US states, Canada, European countries, and Australia).

We then use these spot energy price forecasts to construct pseudo data that “offer numerous advantages compared to conventional time series particularly in that they avoid multicollinearity, a limited sample range, and inadequate technical and environmental detail” (Griffin, 1977, p.112). The resulting pseudo data enable a two-part price responsiveness analysis of solar and wind capacity demands, which is a novel integration of (a) VRE procurement planning under wholesale electricity price uncertainty and (b) price elasticity estimation in the absence of publicly available data for VRE PPA transactions that are commercially sensitive information. To the best of our knowledge, the analysis is unseen in the extant studies of VRE development or those of non-residential electricity demand.

The above noted two-part analysis is inspired by the theory of input demand under input price uncertainty (Wolak and Kolstad, 1991). Part 1 constructs pseudo data by solving the problem of minimizing a LSE’s annual risk-adjusted budget for energy procurement (Woo et al., 2004b). This problem sharply differs from those in electricity finance that propose using electricity derivatives to hedge PPAs (Deng and Oren, 2006). Further, its formulation avoids the nuances of risk aversion analyzed by Menezes and Hanson (1970). Instead, it adopts risk-adjusted budget minimization based on the concept of value at risk commonly used in applied finance (Jorion, 1997).

Part 2 is the econometric modelling of price responsiveness based on our recent studies of commercial electricity demand (Li and Woo, 2022) and industrial electricity demand (Li et al., 2022). It entails estimating a bivariate linear regression with the natural log of (solar capacity demand ÷ wind capacity demand) as the regressand and the natural log of (solar

PPA's energy price \div wind PPA's energy price) as the regressor. We then use the regression results to quantify the extent of substitutability between solar and wind capacities and the own-price elasticities of solar and wind capacity demands.

1.7 Key findings

Our key findings associated with the spot energy price forecasts by TOD based on ERCOT's market data are as follows:

- Reflecting the use of natural gas futures to cross hedge electricity spot price volatility (Woo et al., 2011), our spot energy price forecasts for 2024 are \$34.4/MWh for the daytime period and \$25.6/MWh for the nighttime period. Hence, the daytime energy price forecast of \$34.4/MWh far exceeds the 2021 average forward energy price of \$25/MWh of solar PPAs (Bolinger et al., 2021) and wind PPAs (Wiser et al., 2021). However, the same cannot be said about the nighttime energy price forecast.
- The standard deviations of the 2024 spot energy price forecasts are \$6.8/MWh for the daytime period and \$2.8/MWh for the nighttime period, underscoring a LSE's exposure to spot energy price volatility.
- The spot energy price forecasts and their standard deviations by TOD are similar across the forecast periods of one year, three years, five years, and ten years.

As the energy price forecasts are similar across the four forward-looking periods, variations in the contract periods of short-term VRE PPAs of up to 10 years do not alter the following key findings from our econometric analysis of price responsiveness:

- Solar and wind capacities are close substitutes because the estimate for the elasticity of substitution is 10.99, far exceeding those reported in the commercial electricity demand studies reviewed by Li and Woo (2022) and the industrial electricity demand studies reviewed by Li et al. (2022).

- When solar and wind PPAs have similar energy prices, solar capacity demand is approximately four times wind capacity demand, thus corroborating Texas's projected ratio of solar GW addition to wind GW addition portrayed in Figure 1, as well as those in the US and elsewhere.
- The own-price elasticity estimates are -5.34 for solar capacity demand and -5.65 for wind capacity demand, much larger in size than the US non-residential electricity demand's own-price elasticity estimates of approximately -0.1 found by Woo et al. (2018) and those reported by the plethora of other US and non-US studies reviewed by Li and Woo (2022) and Li et al. (2022).

The key takeaway of the third finding is that price management of solar and wind capacity demands can be highly effective for mitigating large-scale VRE development's adverse effects on Texas's electric grid. Exemplifying these effects are frequent overloading of the transmission lines from the Panhandle and West Texas to load centers in other parts of the state (Cao et al., 2022), exacerbation of natural-gas-fired generation's missing money problem (Zarnikau et al., 2019), dwindling amount of operating reserves (Zarnikau et al., 2020), and highly correlated output levels among renewable power plants within a region, which tends to exacerbate overreliance on VRE development for achieving resource adequacy (Astrapé Consulting, 2022).

The proposals for decelerating Texas's VRE development include a performance credit mechanism that rewards resources available during hours of highest reliability vulnerability, some ancillary services costs to be recovered from VRE suppliers and users, and possible refinements of ERCOT's energy-only wholesale market design (Ming et al., 2022). As adopting these proposals is likely to decelerate the pace of CO₂ reduction, it underscores the policy and regulatory challenges in deep decarbonization of an electric grid with wholesale market competition and large-scale VRE development.

1.8 Linkage to extant studies

A summary of this paper's linkage to extant studies is as follows. First, the paper uses the concept of value at risk (Jorion, 1997) to formulate the budget minimization problem in connection to solar and wind capacity procurement. Second, this formulation is an adaptation of the optimal procurement of conventionally generated energy (Woo et al., 2004b). Finally, the paper is related to the recent studies of VRE purchases by electricity utilities (Carvallo et al., 2020), municipal energy business models (Brinker and Satchwell, 2020), VRE capacity optimization (Simshauser et al., 2022), decarbonization of electricity industries (Morse et al., 2022), regional revenues of solar and wind developers (Woo et al. 2023), an electric grid's integration of VRE (Holtinen et al., 2021), and market economics of VRE supply (Mowers et al., 2023).

1.9 Contributions

To the best of our knowledge, this paper makes four contributions to the literature on VRE procurement and electricity demand estimation. First, it is an initial look at a LSE's procurement of solar and wind capacities that results in solar and wind capacity demands.

Second, its methodology employs pseudo data for estimating solar and wind capacity demands under wholesale spot energy price uncertainty, which is an innovation unseen in extant studies of VRE development or those related to non-residential electricity demand estimation. With minor modifications, it is applicable to other regional transmission organizations (RTOs) in North America, South America, Europe, and Asia-Pacific.

Third, its methodological transparency demonstrated through our completely solved case study of Texas aids the understanding of policy analysts, regulatory staff, and industry practitioners who tend to eschew the technical complexities in a LSE's procurement strategy. A good case in point is the first author's direct and surrebuttal testimonies cited by the report

and decision of the Public Service Commission of Missouri on the prudence of KCP&L's use of natural gas futures to cross hedge spot electricity's price risk (PSCM, 2012).

Finally, its empirics inform the nexus between VRE procurement and development in non-Texas wholesale electricity markets in the US and elsewhere (e.g., Canada, Europe, and Australia), all of which have highly volatile wholesale spot electricity prices and escalating market penetration of VRE generation.

1.10 Organization

The rest of this paper proceeds as follows. Section 2 discusses the paper's real-world relevance in connection to cleaner production. Section 3 describes a 1-year PPA for VRE. Section 4 develops our methodology that encompasses spot energy price forecasting, construction of pseudo data, and econometric analysis of the price responsiveness of solar and wind capacity demands. Section 5 explains our input data construction. Section 6 reports our empirics, the basis for Section 7: conclusions and policy implications. Provided as supplementary information, Appendix 1 lists our paper's caveats that mainly serve to identify several fruitful areas of future research. Finally, Appendix 2 justifies our geographic choice of Texas as our illustrative example.

2. Real-world relevance

A study of cleaner production matters only when it is real-world relevant. Highlighting our paper's real-world relevance are the following remarks. First, a LSE's procurement plan should obey budget minimization, as "money is no object" violates the principle of financial prudence (Woo et al., 2004b).

Second, short-term PPAs for VRE are increasingly popular in the US (Roselund, 2019), possibly because some LSEs worry about the potential for stranded costs due to over-priced long-term PPAs (Woo et al., 2003b) and some VRE developers find short-term PPAs more

profitable than long-term PPAs with forward energy prices that are below the spot energy price forecast (Qi et al., 2024).

Third, a summer-peaking electric grid like Texas's has daytime spot energy prices that are on average higher than nighttime energy prices, as evidenced by ERCOT's market data (Zarnikau et al., 2019). The same can be said about other summer-peaking grids in North America and elsewhere.

Fourth, a solar PPA's per MWh avoided cost of reducing spot energy purchase based on ERCOT's daytime energy prices exceeds a wind PPA's per MWh avoided cost based on the load-weighted average of ERCOT's daytime *and* nighttime energy prices. Hence, when both have similar forward energy prices, a solar PPA is more cost-effective than a wind PPA on a per MWh basis from the perspective of procurement budget minimization. This remark also applies to other summer peaking wholesale electricity markets where the annual average of daytime spot energy prices is higher than that of nighttime spot energy prices.

Finally, as the average energy prices of recently signed solar and wind PPAs equal ~\$25/MWh, they help explain the large 15.2 GW difference between Texas's short-term solar and wind capacity additions. By extension, they corroborate AEO 2023's projected large difference between long-term solar and wind capacity additions in the US when long-term solar and wind PPAs have similar forward energy prices (LevelTen Energy, 2023).

3. Description of a 1-year solar PPA

Matching a LSE's annual budgeting, this section describes a hypothetical 1-year solar PPA as the description of a 1-year wind PPA is entirely analogous. We adopt the 1-year contract period to accentuate the role of short-term PPAs in a LSE's solar capacity procurement, notwithstanding that the contract periods mentioned by Roselund (2019) are between five to seven years. Section 4 shows that extending the PPA period beyond one year

is straightforward, without materially enhancing our understanding of a LSE's optimal procurement problem.

Reflecting the concept of electricity product differentiation (Woo et al., 2014), the solar PPA stipulates must-take energy delivered by the contracted MW of a solar plant's total capacity. The solar PPA's quantity term is MW-based because the plant's actual weather-dependent output is not *a priori* known and can cause contractual ambiguity in the PPA's specification. In short, the solar PPA clearly states the contractual obligations of its buyer and seller, albeit the uncertainty in the solar plant's weather-dependent energy output in the PPA's delivery period.

The solar PPA's physical delivery requirement precludes solar PPA sellers who are (a) energy traders that buy wholesale spot energy and renewable energy credits to meet their supply obligations and (b) independent power producers that use their conventional generation augmented by renewable energy credits. This makes sense for the following reasons. First, such PPA sellers are uncommon. Second, market trading of renewable energy credits is thin with unreliable price discovery. Finally, renewable energy credits do not materially alter the procurement problem, so long as they do not substantially change the forward energy prices of solar PPAs.

The solar PPA differs from a tolling agreement under which the agreement buyer makes an upfront capacity payment to the agreement seller for the right but not the obligation to dispatch the contracted capacity of the underlying natural-gas-fired power plant (Woo et al., 2019). It also differs from a forward contract for a take-or-pay block of non-interruptible power with a 100% delivery rate (Woo et al., 2001). However, it resembles a forward contract for an unspecified amount of as-available energy supply with negligible marginal energy cost, as exemplified by the surplus hydro generation in the Pacific Northwest of the US during the spring runoff season of April through June (Woo et al., 2013).

The solar PPA's MWh delivery depends on the output performance of the underlying solar plant. Specifically, a solar plant's annual daytime capacity factor for the 1-year delivery period is $\alpha = \text{annual total delivery of solar MWh} \div (\text{total MW of contracted capacity} \times \text{number of daytime hours per year})$. Without any loss of generality, we use α here to simplify the notations of the optimal procurement problem. To see this point, consider a solar plant's capacity factor based on annual MWh output (Bolinger et al., 2021). However, Texas's solar generation in the nighttime period is, for all practical purposes, equal to zero (UL Services Group, 2021). Suppose the solar plant's annual capacity factor is $A = \text{average solar MW for the entire year} / \text{total solar MW installed}$. The solar plant's daytime capacity factor is $\alpha \approx 2A$ because the number of daytime hours is half of the total number of hours per year.

There is a strong incentive for a solar plant owner in the US to maximize α by performing regularly scheduled maintenance and timely repair. This is because even if a solar PPA's energy price is relatively low at \$25/MWh, it still far exceeds solar generation's variable O&M cost of under \$10/MWh (Bolinger et al., 2021). Further, the 2022 Inflation Reduction Act of the US offers a federal production tax credit of \$27.5/MWh (Solar Energy Technologies Office, 2023). As a result, the plant's per MWh operating profit is over \$42.5, a sufficiently large incentive for a solar plant owner in the US to maximize α . While non-US solar plant owners may not enjoy generous production tax credits like their US brethren, per MWh operating profits of over \$15 still represent considerably large incentives for maximizing the output performance of solar plants.

4. Methodology

4.1 Spot energy price forecasts

Our methodology begins with constructing $\mu_j = \text{spot energy price forecast for period } j = 1 \text{ for the daytime hours and } 2 \text{ for the nighttime hours}$. Importantly, our easy-to-implement forecasting method is applicable to non-Texas electric grids with similar data availability.

To find μ_j , we use ERCOT's monthly energy price data for the period of Sep-2012 to Aug-2023 (excluding Feb-2021) to estimate a bivariate robust regression that reflects using natural gas futures to cross hedge against spot energy price risk (Woo et al., 2011). We do not employ a bivariate OLS regression because it leads to empirically implausible coefficient estimates, as similarly found by Brown et al. (2020, Appendix 1).

There are two reasons for the regression's underpinning of cross hedging. First, while electricity futures contracts can be used to directly hedge against spot price risk, their trading volume is often zero (CME Group, n.d.). Due to their lack of credible price discovery caused by zero trading, these contracts are not used here for forecasting ERCOT's average spot energy price for the PPA's contract period. Second, our regression-based approach is applicable to wholesale electricity markets that do not have electricity futures price quotes (e.g., the Pacific Northwest and Southwest Power Pool of the US).

With intercept and slope estimates of a_j and b_j , this regression is:

$$P_{jm} = a_j + b_j G_m + e_{jm}, \quad (1)$$

where P_{jm} = average of ERCOT's hourly energy prices for period j in month m = Sep-2012, ..., Aug-2023; G_m = average of daily Henry Hub prices in month m ; and e_{jm} = regression residual for TOD period j in month m . Equation (1) uses monthly data to properly match the reality that a monthly natural gas futures contract's volume is the total amount of natural gas delivered in a future month.

For the daytime period, b_1 is an estimate of the market-based heat rate of natural-gas-fired generation because Texas's daytime marginal fuel is natural gas (Zarnikau et al., 2019). If b_1 is not statistically different from a combined cycle gas turbine's engineering heat rate of 7 MMBtu/MWh, it suggests the daytime empirical plausibility of equation (1). As Texas's nighttime marginal generation fuel can be natural gas, coal, nuclear or wind, a finding of $b_2 < 7$ suggests the nighttime empirical plausibility equation (1).

Based on equation (1), $\mu_j = a_j + b_j G_f$, where G_f = natural gas price forecast for 2024 = average of the monthly natural gas futures prices published on 10/11/2023 by the CME Group for Jan-2024 to Dec-2024. Let σ_G denote the standard deviation of the natural gas futures prices. Because b_j and G_f are stochastic, the variance of μ_j is σ_j^2 , the sum of (1) μ_j 's variance under the assumption that G_f is non-stochastic; (2) $b_j^2 \times \sigma_G^2$ = natural gas futures price's variance magnified by the squared value of natural-gas-fired generation's market-based heat rates by TOD; and (3) variance of $b_j \times \sigma_G^2$ = natural gas futures price's variance magnified by the variance of the market-based heat rates by TOD (Feldstein, 1971). Since the next section requires ρ = correlation of μ_1 and μ_2 , we use the recorded monthly data for P_{1m} and P_{2m} to calculate ρ (Woo et al., 2004b).

4.2 Pseudo data construction

4.2.1 Procurement of solar and wind capacities

Consider a LSE interested in signing 1-year PPAs for K_1 MW of solar capacity and K_2 MW of wind capacity to meet its total VRE capacity target of $K = K_1 + K_2 > 0$. Restricting $K = 0$ renders VRE budgeting unnecessary. However, this restriction contradicts the market reality that retail electricity pricing plans often have VRE content of up to 100% (Brown et al., 2020).

Suppose $\$F_1/\text{MWh}$ and $\$F_2/\text{MWh}$ are the respective forward energy prices of the 1-year solar and wind PPAs based on the supply offers submitted by VRE sellers in response to a LSE's competitive procurement auction (Cai et al., 2022). The wind PPA's single forward energy price of $\$F_2/\text{MWh}$ mirrors the price terms of footnote 10's examples of wind PPAs. As shown in Section 4.3 below, the natural log of the (F_1/F_2) ratio moves the natural log of the optimally chosen (K_1 / K_2) ratio.

4.2.2 Procurement cost expectation and variance

Procurement cost expectation and variance are essential information for determining a LSE's solar and wind capacity demands. Recognizing that solar plants and windfarms have stochastic output performances, our calculation of procurement cost expectation and variance is a recursive two-stage process. Specifically, it starts with calculating the procurement cost realized in Stage 2 when actual MWh deliveries occur. It then assesses the procurement cost expectation and variance in Stage 1 prior to the commencement of Stage 2.

Our Stage 2 calculation uses the following definitions: $\alpha \equiv$ annual daytime solar capacity factor, $\beta \equiv$ annual daytime wind capacity factor, and $\delta \equiv$ annual nighttime wind capacity factor. The daytime and nighttime wind capacity factors differ because Texas's wind generation is lower in the daytime period than in the nighttime period (UL Services Group, 2021). The formulae for calculating β and δ are analogous to the formula for calculating α in Section 3. Since there are 8,760 hours in a non-leap year, wind generation's annual capacity factor is $(\beta + \delta) / 2$, in line with the annual wind capacitor's definition of Wiser et al. (2021) for gauging a windfarm's output performance.

The MWh deliveries *conditional* on the realization of α , β and δ in the leap year of 2024 that has 366 calendar days are as follows:

$$\text{Daytime solar energy delivery} = Q_1 = \alpha K_1 \times 4,392 \text{ daytime hours.} \quad (2)$$

$$\text{Daytime wind energy delivery} = Q_2 = \beta K_2 \times 4,392 \text{ daytime hours.} \quad (3)$$

$$\text{Nighttime wind energy delivery} = Q_3 = \delta K_2 \times 4,392 \text{ nighttime hours.} \quad (4)$$

Suppose the average spot energy prices are P_1 and P_2 for daytime and nighttime wholesale energy purchases in 2024. The annual *ex post net* procurement cost (\$/year) is:

$$\begin{aligned} C &= (F_1 - P_1) Q_1 + (F_2 - P_1) Q_2 + (F_2 - P_2) Q_3 \\ &= 4,392 \times [(F_1 - P_1) \alpha K_1 + (F_2 - P_1) \beta K_2 + (F_2 - P_2) \delta K_2]. \end{aligned} \quad (5)$$

In equation (5), $(F_1 - P_1)$, $(F_2 - P_1)$ and $(F_2 - P_2)$ are *net* per MWh procurement costs, chiefly because P_1 and P_2 are per MWh avoided costs due to VRE delivery's displacement of a LSE's purchase of wholesale spot energy (Sreedharan et al., 2016).

Let $\phi = K_1 / K$ and $(1 - \phi) = K_2 / K$ so that we can rewrite equation (5) as

$$C = 4,392 \times K [\alpha \phi (F_1 - P_1) + \beta (1 - \phi) (F_1 - P_1) + \delta (1 - \phi) (F_2 - P_2)]. \quad (6)$$

Since C is a multiple of K , we assume $K = 1$ to circumvent the information requirement of the LSE's VRE capacity target. Multiplicatively scaling K does not change a LSE's decision on ϕ that we use to characterize the mix of solar and wind capacities procured.

For given values of α , β and δ , our Stage 1 calculation has two steps. The first step entails forecasting C at $K = 1$, implying that the conditional forecast of C is:

$$\mu_C = 4,392 \times [\phi \alpha (F_1 - \mu_1) + (1 - \phi) \beta (F_2 - \mu_1) + (1 - \phi) \delta (F_2 - \mu_2)], \quad (7)$$

where μ_1 = forecast of P_1 and μ_2 = forecast of P_2 (Mood et al., 1974, pp.157-158). As μ_1 and μ_2 are the forecasts for P_1 and P_2 that are average TOD spot energy prices in 2024, μ_C is normally distributed according to the central limit theorem (Mood et al., 1974).

Equation (7) shows that increases in F_1 and F_2 raise μ_C . In contrast, increases in μ_1 and μ_2 reduce μ_C . The marginal effect of ϕ on μ_C can be positive or negative because the sign of $\partial \mu_C / \partial \phi = 4,392 \times [\alpha (F_1 - \mu_1) - \beta (F_2 - \mu_1) - \delta (F_2 - \mu_2)]$ depends on whether $\alpha (F_1 - \mu_1)$ is above or below $[\beta (F_2 - \mu_1) + \delta (F_2 - \mu_2)]$. If $\partial \mu_C / \partial \phi < 0$, a LSE can increase ϕ to reduce μ_C by procuring relatively more solar capacity.

Based on equations (6) and (7), the conditional variance of μ_C is:

$$\begin{aligned} \sigma_C^2 = & 4,392^2 [\phi^2 \alpha^2 \sigma_1^2 + (1 - \phi)^2 \beta^2 \sigma_1^2 + (1 - \phi)^2 \delta^2 \sigma_2^2 + 2 \alpha \beta \phi (1 - \phi) \sigma_1^2 + \\ & 2 \alpha \delta \phi (1 - \phi) \rho \sigma_1 \sigma_2 + 2 \beta \delta (1 - \phi)^2 \rho \sigma_1 \sigma_2], \end{aligned} \quad (8)$$

where σ_1^2 = variance of P_1 , σ_2^2 = variance of P_2 , and ρ = correlation of P_1 and P_2 (Mood et al., 1974). Equation (8) shows that σ_C^2 depends on ϕ so that a LSE can alter ϕ to manage its

exposure to procurement cost volatility. Further, F_1 and F_2 move the risk-adjusted budget defined by equation (11) below because equation (7) demonstrates μ_C 's dependence on F_1 and F_2 .

The second step of our Stage 1 calculation recognizes α , β and δ are random variables with values that are unknown prior to contract signing of solar and wind PPAs. Let $\pi_n =$ probability of event n for $n = 1, \dots, N$ characterized by three capacity factor intervals. Specifically, event 1 is $(0.0 < \alpha \leq 0.2, 0.0 < \beta \leq 0.2, 0.0 < \delta \leq 0.2)$, event 2 is $(0.2 < \alpha \leq 0.4, 0.0 < \beta \leq 0.2, 0.0 < \delta \leq 0.2)$, ..., and event $N = 125$ is $(0.8 < \alpha \leq 1.0, 0.8 < \beta \leq 1.0, 0.8 < \delta \leq 1.0)$.

As event n is driven by the engineering designs of solar plants and windfarms and weather conditions of sunniness and windiness, it is statistically independent of the cost forecast and variance of a LSE's VRE procurement. Said equivalently, VRE contracts signed before the actual commencement of energy delivery cannot alter the physical attributes of VRE power plants already installed nor the weather conditions in the subsequent period of energy delivery.

Let μ_{Cn} and σ_{Cn}^2 denote the event-specific μ_C and σ_C^2 based on event n 's midpoints of the three capacity factor intervals. The ordered triple $(0.1, 0.1, 0.1)$ is event 1's midpoints, ..., $(0.9, 0.9, 0.9)$ is event 125's midpoints. Using the midpoints makes sense for two reasons. First, it circumvents the potential problem that some of the capacity factor intervals may have very few observations that can render a mean estimate unreliable. Second, if a capacity factor interval contains symmetrically distributed data, the interval's midpoint and mean coincide.

The **unconditional** cost forecast θ and cost variance σ_θ^2 can now be found as probability-weighted averages (Mood et al., 1974, pp.157-158):

$$\theta = \sum_n \pi_n \mu_{Cn}, \tag{9}$$

$$\sigma_\theta^2 = \sum_n \pi_n \sigma_{Cn}^2. \tag{10}$$

4.2.3 Effects of forward price premium and discount on VRE procurement

When F_1 in equation (7) is higher (lower) than μ_1 , a solar PPA contains a forward price premium = $F_1 - \mu_1 > 0$ (discount = $F_1 - \mu_1 < 0$). As noted by an insightful reviewer, a LSE is unlikely (likely) to sign a solar PPA with a forward price premium (discount).

The plausible reasons for a solar PPA's forward price premium include (a) a LSE is more conservative than solar developers when making management decisions (DeBenedictis et al., 2011); (b) a LSE has a high VRE procurement target in pursuance of carbon neutrality by 2050 (Gee et al, 2022); and (c) there are relatively few VRE developers participating in a LSE's procurement auction (Klemperer, 2002). In contrast, a solar PPA's forward price discount reflects solar developers bidding aggressively to secure forward energy sales in response to a LSE's procurement auction (Qi et al., 2024).

We now state a wind PPA's forward price premium and discount for the following three cases: (1) $F_2 > \mu_1 > \mu_2$ so that the wind PPA's daytime premium is $(F_2 - \mu_1) > 0$ and nighttime premium is $(F_2 - \mu_2) > 0$; (2) $\mu_1 > F_2 > \mu_2$ so that the wind PPA's daytime discount is $(F_2 - \mu_1) < 0$ and nighttime premium is $(F_2 - \mu_2) > 0$; and (3) $\mu_1 > \mu_2 > F_2$ so that the wind PPA's daytime forward price discount is $(F_2 - \mu_1) < 0$ and nighttime discount is $(F_2 - \mu_2) < 0$. A LSE is likely to sign a wind PPA that has daytime and nighttime forward price discounts.

In summary, when both F_1 and F_2 embody forward price discounts, a LSE tends to sign the associated solar and wind PPAs because these discounts imply the expected cost of VRE procurement is negative so that VRE procurement is *ex ante* profitable. However, a LSE's preferred mix of solar and wind capacities remains unknown, thus motivating the procurement problem stated in the next section.

4.2.4 Risk-adjusted budget minimization

We use equations (9) and (10) to define a LSE's risk-adjusted procurement budget:

$$B = \theta + 1.65 \sigma_\theta, \quad (11)$$

which exceeds the actual procurement cost that may occur in the 1-year contract period with a 0.95 probability under the assumption that θ is normally distributed (Jorion, 1997). As equation (11) does not require knowing a LSE's degree of risk aversion (Menezes and Hanson, 1970), it enables a practical derivation of solar and wind capacity demands.

Resembling a competitive firm's cost-minimizing behavior (Varian, 1992), a LSE chooses ϕ^* , which is the ϕ value between 0.0 and 1.0 that minimizes B (Woo et al., 2004b). Without using nonlinear programming to find the interior and corner solutions for ϕ^* (Woo et al., 2004b), we propose a simple grid search that entails the following steps:

- (1) Calculate θ and σ_θ for ϕ between 0.0 and 1.0 for a specific pair of F_1 and F_2 . Since ϕ may equal 0.0, 0.01, ..., 0.99, or 1.0, there are 12,625 combinations of ϕ , μ_{Cn} and σ_{Cn} (i.e., 101 solar capacity shares \times 125 events defined by the three capacity factor intervals). Thanks to the probability-weighted averaging shown by equations (9) and (10), each ϕ value yields one combination of θ and σ_θ , implying that there are 101 values for $B = \theta + 1.65 \sigma_\theta$ according to equation (11).
- (2) Find ϕ^* between 0.0 to 1.0 that yields $B^* = \text{minimum value of } B \text{ for the pair of } F_1 \text{ and } F_2$ in step (1). The grid search for ϕ^* is remarkably simple because $B^* = \min(B \text{ evaluated at } \phi = 0.0, \dots, B \text{ evaluated at } \phi = 1.0)$, and ϕ^* is the ϕ value associated with B^* .
- (3) Repeat step (2) for all possible pairs of F_1 and F_2 listed in Section 5 below to obtain the corresponding values for ϕ^* and B^* . While Section 5 shows that the number of plausible pairs of F_1 and F_2 can be quite large, this step's computation time is under one second, attesting to our methodology's practicality in real-world applications.

4.3 Econometric analysis of price responsiveness

Inspired by the econometric analysis of pseudo data (Griffin, 1977), we assume a constant-elasticity-of-substitution (CES) procurement cost function that is homogeneous of

degree one in K (Varian, 1992). In other words, multiplicatively scaling K by a positive factor magnifies the LSE's procurement cost by the same factor.

As shown by a commercial electricity demand analysis (Li and Woo, 2022), the CES specification enables us to estimate the following OLS regression with intercept λ_0 and random error ε :

$$\ln[\phi^* / (1 - \phi^*)] = \lambda_0 + \lambda_1 \ln(F_1 / F_2) + \varepsilon. \quad (12)$$

Equation (12) shows that the regressand is the natural log of (solar capacity demand \div wind capacity demand) because $\phi = K_1 / K$ and $(1 - \phi) = K_2 / K$, and the regressor is the natural log of (solar PPA's energy price \div wind PPA's energy price). As $\ln[\phi^* / (1 - \phi^*)]$ is undefined at $\phi^* = 0.0$ and equals infinity at $\phi^* = 1.0$, we set $\phi^* = 0.0$ to 0.01 and $\phi^* = 1.0$ to 0.99 when using OLS to estimate equation (12). We perform robust and Tobit regressions to verify that the OLS results are insensitive to the choice of estimation method.

We use λ_0 to determine if equation (12) is a plausible explanation for the explosive growth in solar capacity addition. To see this point, let Y denote the expected value of $\ln[\phi^* / (1 - \phi^*)]$. When $F_1 = F_2$, $\ln(F_1 / F_2) = 0$ and $Y = \lambda_0$. Recall that 4.3 is Texas's projection of (solar capacity addition \div wind capacity addition). Hence, if λ_0 is close to $\ln(4.3) = 1.46$, it suggests Texas's solar capacity addition will continue to dwarf wind capacity addition under the condition of $F_1 = F_2$. The same suggestion corroborates AEO's projection that solar capacity addition will be about three times wind capacity addition in the US because the recently signed solar and wind PPAs have similar forward energy prices (LevelTen Energy, 2023).

We now turn our attention to $\lambda_1 = -\partial \ln(K_1 / K_2) / \partial \ln(F_2 / F_1) = -1 \times$ elasticity of substitution between K_1 and K_2 (Varian, 1992). We expect $\lambda_1 < 0$ because a marginal decrease in (F_1 / F_2) causes a LSE to procure relatively more solar capacity than wind capacity. As a result, solar capacity is a substitute for wind capacity in VRE procurement planning, and the

extent of substitutability is measured by the size of λ_1 . We expect λ_1 's size to be large, chiefly because a LSE's *ex ante* decision making can be highly responsive to a small change in (F_1 / F_2) . Had equation (12) been estimated using *ex post* market data, the size of λ_1 could be quite small. This is because these market data are based on the set of solar and wind PPAs already signed, not the much larger set of possible solar and wind PPAs considered by a LSE before contract signing.

We expect a LSE's solar capacity demand to be price-elastic as λ_1 's size is likely large. This is because the own-price elasticity of solar capacity demand is $E_{11} = \partial \ln K_1 / \partial \ln F_1 = \lambda_1 (1 - W_1) < 0$, where $W_1 = \text{solar capacity cost share} = \phi^* F_1 / [\phi^* F_1 + (1 - \phi^*) F_2]$ (Cao et al., 2023). The solar cross-price elasticity is $E_{12} = \partial \ln K_1 / \partial \ln F_2 = -E_{11} > 0$ because simultaneously changing F_1 and F_2 by one percent does not alter the solar capacity demand. To see this point, consider $\Delta \ln K_1 = E_{11} \Delta \ln F_1 + E_{12} \Delta \ln F_2$. When $\Delta \ln F_1 = \Delta \ln F_2 = 1\%$, it does not change the (F_1/F_2) ratio, thus implying $\Delta \ln K_1 = 0$ and $E_{11} + E_{12} = 0$.

We also expect a LSE's wind capacity demand to be price-elastic because the own-price elasticity of wind capacity demand is $E_{22} = \partial \ln K_2 / \partial \ln F_2 = \lambda_1 (1 - W_2) < 0$, where $W_2 = \text{wind capacity cost share} = (1 - \phi^*) F_2 / [\phi^* F_1 + (1 - \phi^*) F_2]$. The wind cross-price elasticity is $E_{21} = \partial \ln K_2 / \partial \ln F_1 = -E_{22} > 0$.

Finally, E_{11} and E_{22} are nonlinear in W_1 because $W_1 + W_2 = 1$. Hence, their average values are the respective sample means of observation-specific estimates (Cao et al., 2023).

5. Input data construction

We first construct the probability π_n for event n . As an illustration, we use a sample of 47 solar plants and 272 windfarms already in commercial operation in Texas to obtain event n 's relative frequency, which serves as an estimate of π_n (Mood et al., 1974).

We now construct the plausible pairs of F_1 and F_2 used by the grid searches for ϕ^* in each of the following scenarios of interest:

- (1) $F_1 = F_2 = \$25/\text{MWh}$, which is the average forward energy price of recently signed PPAs for VRE.
- (2) $F_1 = F_2 = \$50/\text{MWh}$, which is the US average forward energy price of the PPAs for VRE in the first quarter of 2023 (LevelTen Energy, 2023).
- (3) Alternative pairs of F_1 and F_2 , where F_1 's range is $\mu_1 \pm \sigma_1$ for a solar PPA; and F_2 's range is $\nu \pm \sigma_\nu$ for a wind PPA, with $\nu = S \mu_1 + (1 - S) \mu_2$, $\sigma_\nu^2 = S^2 \sigma_1^2 + S(1 - S) \rho \sigma_1 \sigma_2 + (1 - S)^2 \sigma_2^2$, and $S = 0.436 = \text{ERCOT's total daytime wind MWh} \div \text{ERCOT's total wind MWh}$ (Woo et al., 2023). We choose these two ranges to capture the forward price discounts/premia that may exist in the PPA price offers of VRE sellers. Further, we use each range to find 100 equally separated VRE energy prices. Suppose the range is \$25/MWh to \$50/MWh for a solar PPA. The first F_1 value is \$25/MWh, the second F_1 value is $\$25/\text{MWh} + (\$50/\text{MWh} - \$25/\text{MWh}) / 99 = \$25.2525/\text{MWh}$, ..., the last value is \$50/MWh. As a result, the total number of possible combinations of F_1 and F_2 is $100 \times 100 = 10,000$ based on a full factorial design.

Scenario (3) encompasses the next three scenarios related to the forward price discounts and premia of VRE PPAs. Based on the price forecast results reported in Section 6, these scenarios are as follows:

- (4) $F_1 = \mu_1 - \sigma_1 = \$27.59/\text{MWh}$ and $F_2 = \nu - \sigma_\nu = \$25.54/\text{MWh}$ that reflect the forward price discounts of σ_1 and σ_ν due to aggressive bidding by VRE developers participating in the LSE's procurement auction. Hence, F_1 is moderately larger than and F_2 is remarkably close to the average PPA price of \$25/MWh.
- (5) $F_1 = \mu_1 = \$34.4/\text{MWh}$ and $F_2 = \nu = \$29.43/\text{MWh}$ that do not have forward price premia or discounts. As F_1 and F_2 exceed those in scenario (4), they increase θ that measures a LSE's procurement cost forecast.

(6) $F_1 = \mu_1 + \sigma_1 = \$41.21/\text{MWh}$ and $F_2 = \nu + \sigma_\nu = \$33.31/\text{MWh}$ that reflect the forward price premia of σ_1 and σ_ν . Further, F_1 is numerically close to the average price of $\sim \$40/\text{MWh}$ for Texas's solar PPAs in the first quarter of 2023 (LevelTen Energy, 2022). Although these F_1 and F_2 exceed those in scenario (5), Section 4.2.1 explains that a LSE still procures the associated solar and wind PPAs to meet its total VRE capacity target in support of its retail pricing plans.

6. Empirics

6.1 Solar and wind capacity factors

Panel A of Table 1 presents the descriptive statistics of the plant-level annual capacity factor data used to compute the relative frequencies presented in Panel B. Emerged from Panel A are the following remarks:

- The difference in the number of observations between solar and wind generation reflects (a) the 47 solar plants have relatively late dates of commercial operation; and (b) the number of wind farms is 272, which is 5.79 times the number of solar plants.
- Solar generation's average daytime capacity factor (CF) of 0.51 exceeds wind generation's average daytime and nighttime CF s of 0.31 and 0.41, thus affirming that solar generation can on a per MW basis better serve Texas's daytime loads than wind generation.
- While the CF s exhibit wide ranges, their standard deviations are equal to ~ 0.1 .
- Most of the 125 events have relative frequencies very close to zero, as only eleven events have relative frequencies above 1%.
- In line with the mean CF s reported in Panel A, the two events of $(0.4 < \alpha \leq 0.6, 0.2 < \beta \leq 0.4, 0.4 < \delta \leq 0.6)$ and $(0.4 < \alpha \leq 0.6, 0.2 < \beta \leq 0.4, 0.2 < \delta \leq 0.4)$ have relative frequencies of 36.44% and 26.34% respectively.

6.2 Spot energy price forecasts by time of day

Figure 2 visually displays the monthly averages of daytime and nighttime spot energy prices, as well as the monthly averages of the Henry Hub natural gas prices. While the daytime and nighttime energy prices tend to move in tandem, they are less correlated with the Henry Hub natural gas prices.

Table 2 presents the descriptive statistics for the monthly data used in our spot energy price regression analysis. Emerged from Table 2 are the following remarks:

- The monthly averages of daytime hourly spot energy prices are volatile, as indicated by their mean of \$37.47/MWh and standard deviation of \$24.93/MWh.
- The monthly averages of nighttime daytime hourly spot energy prices are also volatile, as indicated by their mean of \$26.93/MWh and standard deviation of \$15.42/MWh.
- The monthly average of daily Henry Hub natural gas prices has a mean of \$3.35/MMBtu and a standard deviation of \$1.34/MMBtu. As natural gas is ERCOT's dominant marginal generation fuel, volatile natural gas prices imply volatile spot energy prices.
- Daytime and nighttime energy prices are strongly correlated ($r = 0.84$). However, their correlations with natural gas prices are relatively weak ($r < 0.58$), presaging the possibly limited cross-hedging effectiveness of natural gas futures (DeBenedictis et al., 2011).

The preceding remarks doubt whether equation (1) can reasonably characterize the data generation process for the monthly energy prices by TOD. Thankfully, the answer is yes based on the regression results presented below.

Table 3 reports the OLS regression results based on equation (1) and monthly data described in Table 2. The adjusted R^2 for the daytime and nighttime regressions are 0.71 and 0.95, respectively, indicating that these regressions have reasonable goodness of fit. The daytime regression's intercept estimate is \$6.99/MWh, higher than the nighttime regression's intercept estimate of \$1.87/MWh. Measuring ERCOT's market-based heat rates by TOD, the slope coefficient estimates are 7.57 for the daytime period and 6.55 for the nighttime period.

Since a combined-cycle gas turbine's engineering-based heat rate is 7 MMBtu per MWh, the parsimonious specification of equation (1) is deemed empirically reasonable.

Panel A of Table 4 presents the descriptive statistics of the natural gas futures prices used to construct the spot energy price forecasts by forecast period. It shows that these prices are similar across the four forecast periods. Panel B shows that the daytime energy price forecasts range from \$34.40/MWh to \$36.58/MWh, higher than the nighttime forecasts of \$25.58/MWh to \$27.46/MWh. The daytime forecasts exhibit greater variability than the nighttime forecasts, as indicated by their higher coefficients of variation (= standard deviation / mean). Finally, these TOD forecast results are similar across the four forecast periods due to the similarity among the period-specific natural gas futures price data described in Panel A.

6.3 Results from risk-adjusted budget minimization for five pairs of F_1 and F_2

The fourth column of Table 5 reports the results for ϕ^* for five pairs of F_1 and F_2 . When $F_1 = F_2 = \$25/\text{MWh}$ (or $\$50/\text{MWh}$), $\phi^* = 0.61$ (or 1.0), thus hinting the future disparity between short-term solar and wind capacity additions.

The last column of Table 5 reports the results for B^* for five pairs of F_1 and F_2 . As expected, B^* increases with F_1 and F_2 . Hence, B^* 's lower bound is \$1,962 for the first pair of $F_1 = F_2 = \$25/\text{MWh}$. The B^* 's upper bound is \$59,018 for the second pair of $F_1 = F_2 = \$50/\text{MWh}$, a possible cause for the recent cooling of the US market for VRE PPAs (Penrod, 2023).

6.4 Results from the econometric analysis of price responsiveness

Panel A of Table 6 reports the pseudo data's summary statistics that indicate the large data variations necessary for the precise estimation of equation (12). Emerged from the OLS regression results in Panel B are the following remarks:

- The regressand's mean of $\ln[\phi^* / (1 - \phi^*)]$ is -0.22, implying that the average ϕ^* is 0.445, virtually the same as ϕ^* 's mean of 0.45 in Panel A.

- Despite the remarkably parsimonious specification of equation (12), the adjusted R^2 is 0.90, thus indicating an eminently reasonable goodness of fit for a large cross-sectional sample of 10,000 observations.
- The intercept estimate is 1.36, which suggests equation (12)'s empirical plausibility based on the discussion of λ_0 in Section 4.3. This is because when $F_1 = F_2$ so that $\ln(F_1 / F_2) = 0$, the estimate for $\ln[\phi^* / (1 - \phi^*)]$ is 1.36 so that the estimate for ϕ^* is 0.80. As a result, the estimated solar capacity demand at $F_1 = F_2$ is about four times wind capacity demand, closely in line with Texas's short-term solar capacity addition being 4.3 times wind capacity addition shown in Figure 1.
- The slope estimate for $\ln(F_1 / F_2)$ is -10.99. Based on the discussion of λ_1 in Section 4.3, its large size suggests that solar and wind capacities are close substitutes.
- The LSE's solar and wind capacity demands are very price-elastic, as indicated by their respective own-price elasticity estimates of -5.34 and -5.65.

The remainder of Panel B reports the results of the robust and Tobit regressions that yield elasticity estimates that bookend those obtained from the OLS regression. As a result, the choice of estimation method does not alter our finding that solar and wind capacities are close substitutes and their demands are highly price-elastic.

6.5 Results based on the price quotes for electricity futures

Our energy price forecasts may seem low according to the CME Group's electricity futures price quotes published on 10/11/2023 for daytime delivery at ERCOT's North 345 kV Hub in the 12-month period of Jan-2024 to Dec-2024. However, these monthly price quotes are only indicative because the period does not have monthly futures trading volumes.

The monthly daytime price quotes have a mean of \$50.02/MWh and a standard deviation of \$16.02/MWh. The nighttime period's mean and standard deviation are those of the daytime period multiplied by 0.897, which is ERCOT's most recent TOD price ratio =

average nighttime energy price in Sep-2022 to Aug-2023 \div average daytime energy price in Sep-2022 to Aug-2023 (Woo et al., 2001).

We repeat the budget minimization exercise based on the electricity futures prices quotes, thereby demonstrating how our empirics presented thus far can be revised using an alternative approach for energy price forecasting.

Table 7 reports ϕ^* and B^* for the five pairs of F_1 and F_2 based on the monthly price quotes for electricity futures. The revised range of ϕ^* is 0.57 to 0.82, indicating that a LSE tends to buy more solar capacity than wind capacity. The revised range of B^* is -\$4,115 to \$91,429, suggesting that a high spot energy price forecast can reduce or increase the LSE's risk-adjusted budget, depending on the sizes of F_1 and F_2 .

Table 8 reports the regressions based on the revised forecast results. It shows that the intercept estimates resemble those in Panel B of Table 6. Further, solar and wind capacities are close substitutes because λ_1 's estimates are between -7.1 and -11.8. Finally, solar and wind capacity demands remain highly price-elastic based on their own-price elasticity estimates of -5.2 and -2.9.

7. Conclusions and implications

Our conclusions are as follows. First, when the solar and wind PPAs have forward price premia (discounts), they increase (decrease) the annual budget for VRE procurement and, therefore, discourage (encourage) a LSE from signing these PPAs. Second, solar and wind capacities are close substitutes based on the large elasticity of substitution estimates of up to 11.0 reported in Sections 6.4 and 6.5. Third, when solar and wind PPAs have similar energy prices, solar capacity demand is about four times wind capacity demand, thus rationalizing the Texas and the US projected ratios of solar capacity addition to wind capacity addition. Fourth, solar and wind capacity demands are highly price responsive because Sections 6.4 and 6.5 report that their respective own-price elasticity estimates have sizes far above 1.0.

Finally, as the spot energy price forecasting results are similar for the forward-looking periods of one year, three years, five years, and ten years, extending the procurement horizon beyond one year does not alter the interpretation of the empirics based on 1-year solar and wind PPAs.

There are three implications of the above conclusions. First, as its procurement budget varies with the forward energy prices of solar and wind PPAs, a LSE should regularly revise its procurement plan in response to an electric grid's fast-changing market conditions that move the spot energy price forecasts and the forward energy prices of solar and wind PPAs.

Second, price-elastic solar and wind capacity demands in the presence of declining solar and wind energy prices help explain Texas's large solar and wind capacity additions, thus lending support to the proposals for slowing down Texas's VRE development (Ming et al., 2022). The same can be said about similar proposals considered by non-Texas regions in the US and elsewhere.

Finally, LSEs tend to procure relatively more solar capacity than wind capacity when solar and wind PPAs have similar energy prices, thus alleviating some of the concerns of Texas's policymakers and public utility commission. This implication applies to other electric grids around the world that have system characteristics like those of the Texas grid (e.g., summer peaking demand, high market penetration of VRE generation, natural gas as the dominant marginal generation fuel, dwindling operating reserves, and interzonal transmission constraints).

The key takeaway from the large own-price elasticity estimates is that price management of solar and wind capacity demands can be highly effective, which leads to our policy recommendation of raising the forward prices of solar and wind energy to decelerate VRE development. For example, an ISO may impose a per MWh charge on VRE production that increases the cost for ancillary services. This charge tends to raise the forward prices for

solar and wind energy because VRE generators are inclined to recover the newly imposed cost in their pricing of solar and wind PPAs. The resulting forward energy price increases cause reductions in solar and wind capacity demands. Alternatively, an ISO may require solar and wind developers to firm up their energy deliveries with fast ramping resources like dispatchable battery storage systems that have become increasingly popular due to their cost declines and performance improvements. As the firm-up requirement likely increases the per MWh costs of solar and wind developers, it tends to raise the forward energy prices of solar and wind PPAs.

While adopting our recommendation mitigates VRE generation's adverse effects on an electric grid, it also slows the grid's pace of decarbonization, thus underscoring the policy and regulatory challenges in the quest for clean and sustainable electricity. Hopefully, these challenges will diminish over time owing to the ongoing and still growing R&D on cleaner production in connection to an electric grid's cost-effective and reliable integration of high market penetration of VRE generation.

In closing, we remark that price management of solar and wind capacity demands is a topic of policy debate that deserves the attention of an electric grid's stakeholders. According to the electricity market design study of Woo et al. (2019), a partial list of these stakeholders includes environmentalists and public policy analysts who advocate a clean and sustainable future, regulators and policymakers who pursue clean and reliable electricity service at competitive prices, economists who focus on market demands and supplies, industry practitioners who worry about an electric grid's operation and system reliability, financial analysts who assess investment risks and return, LSEs that aim to best serve their retail customers, retail customers that welcome price stability and price reasonableness, and independent power producers and VRE developers that aim to optimize their financial performances.

CRedit authorship contribution statement

C.K. Woo: Conceptualization, Methodology, Project administration, Writing – original draft, Writing – review & editing. **K.H. Cao:** Formal analysis, Software, Writing – original draft, Writing – review & editing. **H.S. Qi:** Formal analysis, Software, Visualization, Writing – original draft, Writing – review & editing. **J. Zarnikau:** Conceptualization, Writing – original draft, Writing – review & editing. **R. Li:** Visualization, Writing – original draft, Writing – review & editing.

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Table 1. Events with relative frequency $\geq 0.1\%$, with each event defined by the capacity factor (CF) intervals of α , β and δ

Panel A. Descriptive statistics of the annual CF data used to construct Panel B

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
α = solar generation's daytime CF	128	0.51	0.09	0.15	0.69
β = wind generation's daytime CF	1193	0.31	0.08	0.00	0.51
δ = wind generation's nighttime CF	1193	0.41	0.11	0.00	0.67

Notes: (1) The annual CF data are based on 47 solar plants and 272 windfarms in commercial operation from 2016 to 2021.

(2) Each VRE plant's annual CF by time of day in year t is the plant's total MWh by time of day in year t divided by the plant's year-end installed capacity in year $t \times 4,380$ hours (or 4,392 hours for leap years). If the plant does not have complete MWh data for year t , it is excluded in its year t 's CF calculation.

Panel B. Relative frequency of each event

Event ID	Solar daytime CF interval	Wind daytime CF interval	Wind nighttime CF interval	Relative frequency
3	0.4 < α \leq 0.6	0.0 < β \leq 0.2	0.0 < δ \leq 0.2	0.34%
7	0.2 < α \leq 0.4	0.2 < β \leq 0.4	0.0 < δ \leq 0.2	0.33%
8	0.4 < α \leq 0.6	0.2 < β \leq 0.4	0.0 < δ \leq 0.2	2.88%
9	0.6 < α \leq < α \leq	0.2 < β \leq 0.4	0.0 < δ \leq 0.2	0.27%
13	0.4 < α \leq 0.6	0.4 < β \leq 0.6	0.0 < δ \leq 0.2	0.34%
27	0.2 < α \leq 0.4	0.0 < β \leq 0.2	0.2 < δ \leq 0.4	0.36%
28	0.4 < α \leq 0.6	0.0 < β \leq 0.2	0.2 < δ \leq 0.4	3.15%
29	0.6 < α \leq 0.8	0.0 < β \leq 0.2	0.2 < δ \leq 0.4	0.30%
31	0.0 < α \leq 0.2	0.2 < β \leq 0.4	0.2 < δ \leq 0.4	0.25%
32	0.2 < α \leq 0.4	0.2 < β \leq 0.4	0.2 < δ \leq 0.4	3.01%
33	0.4 < α \leq 0.6	0.2 < β \leq 0.4	0.2 < δ \leq 0.4	26.34%
34	0.6 < α \leq 0.8	0.2 < β \leq 0.4	0.2 < δ \leq 0.4	2.51%
37	0.2 < α \leq 0.4	0.4 < β \leq 0.6	0.2 < δ \leq 0.4	0.36%
38	0.4 < α \leq 0.6	0.4 < β \leq 0.6	0.2 < δ \leq 0.4	3.15%
39	0.6 < α \leq 0.8	0.4 < β \leq 0.6	0.2 < δ \leq 0.4	0.30%
52	0.2 < α \leq 0.4	0.0 < β \leq 0.2	0.4 < δ \leq 0.6	0.50%

53	0.4	$< \alpha \leq$	0.6	0.0	$< \beta \leq$	0.2	0.4	$< \delta \leq$	0.6	4.35%
54	0.6	$< \alpha \leq$	0.8	0.0	$< \beta \leq$	0.2	0.4	$< \delta \leq$	0.6	0.41%
56	0.0	$< \alpha \leq$	0.2	0.2	$< \beta \leq$	0.4	0.4	$< \delta \leq$	0.6	0.35%
57	0.2	$< \alpha \leq$	0.4	0.2	$< \beta \leq$	0.4	0.4	$< \delta \leq$	0.6	4.16%
58	0.4	$< \alpha \leq$	0.6	0.2	$< \beta \leq$	0.4	0.4	$< \delta \leq$	0.6	36.44%
59	0.6	$< \alpha \leq$	0.8	0.2	$< \beta \leq$	0.4	0.4	$< \delta \leq$	0.6	3.47%
62	0.2	$< \alpha \leq$	0.4	0.4	$< \beta \leq$	0.6	0.4	$< \delta \leq$	0.6	0.50%
63	0.4	$< \alpha \leq$	0.6	0.4	$< \beta \leq$	0.6	0.4	$< \delta \leq$	0.6	4.35%
64	0.6	$< \alpha \leq$	0.8	0.4	$< \beta \leq$	0.6	0.4	$< \delta \leq$	0.6	0.41%
83	0.4	$< \alpha \leq$	0.6	0.2	$< \beta \leq$	0.4	0.6	$< \delta \leq$	0.8	0.50%
Sum of relative frequencies of the above events										99.33%

Notes: (1) For brevity, Panel B omits events with relative frequency $\leq 0.1\%$. The events in **bold** have relative frequency $\geq 1\%$.

(2) Each event's relative frequency is based on the following steps: (a) use a full factorial design to find all possible combinations of annual CF by time-of-day period, year and VRE plant ID; (b) assign each combination to an event based on the combination's CF values; (c) find M = each event's frequency based on the event's total count of assigned combinations; (d) find N = total frequency of all events; and (e) find (M / N) = each event's relative frequency.

Table 2. Descriptive statistics; sample period = Sep-2012 to Aug-2023, excluding Feb-2021 due to Winter Storm Uri; sample size = 131

Variable	Mean	Standard deviation	Minimum	Maximum	Correlation matrix		
					(1)	(2)	(3)
(1) Monthly averages of hourly daytime spot energy prices (\$/MWh)	37.47	24.93	16.94	215.93	1.0	0.8388	0.4559
(2) Monthly averages of hourly nighttime spot energy prices (\$/MWh)	26.93	15.42	12.47	142.26		1.0	0.5794
(3) Monthly averages of daily Henry Hub natural gas prices (\$/MMBtu)	3.35	1.34	1.63	8.81			1.0

Table 3. Robust energy price regressions by time of day based on equation (1) and monthly data described in Table 2

Variable	Daytime regression			Nighttime regression		
	Estimate	Standard error	<i>p</i> -value	Estimate	Standard error	<i>p</i> -value
Regressand's mean (\$/MWh)	37.47			26.93		
Adjusted R^2	0.714			0.951		
RMSE	6.421			1.988		
Intercept	6.99	1.51	< 0.001	1.87	0.47	< 0.001
Slope coefficient	7.57	0.42	< 0.001	6.55	0.13	< 0.001

Notes: (1) We abandon OLS that does not yield empirically plausible slope coefficient estimates.

(2) The daytime regression's lower adjusted R^2 and higher RMSE reflect that the monthly averages of daytime hourly energy prices are more volatile and less correlated with the monthly averages of daily Henry Hub natural gas prices than those of nighttime hourly energy prices.

(3) We cannot reject at the 5% significance level the hypothesis that the market-based heat rates based on the slope coefficients equal a combined cycle gas turbine's engineering-based heat rate of 7 MMBtu per MWh.

Table 4. Energy price forecasts (\$/MWh) based on equation (1)

Panel A: Descriptive statistics for monthly natural gas futures prices (\$/MMBtu) downloaded on 10/11/2023

Forecast period	Number of observations	Mean	Standard deviation	Minimum	Maximum
1 year: 2024	12	3.620	0.289	3.266	4.301
3 years: 2024 to 2026	36	3.908	0.413	3.266	4.903
5 years: 2024 to 2028	60	3.905	0.437	3.266	4.903
10 years: 2024 to 2033	120	3.853	0.426	3.266	4.903

Source: <https://www.cmegroup.com/markets/energy/natural-gas/natural-gas.html>

Panel B: Energy price forecast results by forecast period and time of day

Variable	Forecast period							
	1 year: 2024		3 years: 2024 to 2026		5 years: 2024 to 2028		10 years: 2024 to 2033	
	Daytime	Nighttime	Daytime	Nighttime	Daytime	Nighttime	Daytime	Nighttime
Forecast = $a_j + b_j G_f$, where $j = 1$ for daytime and 2 for nighttime; and G_f = mean of the monthly natural futures prices from Panel A	34.40	25.58	36.58	27.46	36.56	27.44	36.16	27.10
Forecast's standard deviation = σ_j	6.808	2.751	7.171	3.365	7.252	3.492	7.211	3.430
Forecast's variance = Sum of the three components listed below	46.351	7.567	51.418	11.322	52.590	12.197	52.004	11.766
(1) Variance under the assumption that G_f is non-stochastic	41.550	3.985	41.591	3.989	41.591	3.989	41.581	3.988
(2) $b_j^2 \times \sigma_G^2$, where σ_G = standard deviation of natural gas futures prices in Panel A	4.786	3.581	9.797	7.330	10.965	8.204	10.391	7.775
(3) Variance of $b_j \times \sigma_G^2$	0.015	0.001	0.030	0.003	0.034	0.003	0.032	0.003

Note: The energy price forecasts and their standard deviations by time of day are similar across the four forecast periods.

Table 5. Results for ϕ^* = optimal solar capacity share and B^* = minimum risk-adjusted budget based on five pairs of F_1 and F_2 that reflect the 2024 price forecast result in Table 4

Description	F_1	F_2	ϕ^*	B^*
(1) Average forward energy prices of recently signed VRE PPAs (Bolinger et al., 2021; Wiser et al., 2021)	25	25	0.61	1,962
(2) Average forward energy prices of the US VRE PPAs in the first quarter of 2023	50	50	1.00	59,018
(3) Forward price discounts due to aggressive bidding by VRE developers participating in a LSE's procurement auction	27.59	25.54	0.51	5,834
(4) Forward energy prices without discounts/premia under the efficient market hypothesis	34.40	29.43	0.43	19,179
(5) Forward price premia due to the reasons stated below equation (7)	41.21	33.31	0.36	32,332

Table 6. Regression analysis of price responsiveness based on equation (12) and the 2024 energy price forecast results in Table 4; number of observations = 10,000 based on a full factorial design that yields all possible pairs of F_1 and F_2

Panel A: Pseudo data's summary statistics

Variable	Mean	Standard deviation	Minimum	Maximum
B^* = minimum risk adjusted budget per year	17,596	5,783	5,834	32,332
ϕ^* = optimal solar capacity share	0.45	0.28	0.00	1.00
F_1 = solar PPA's forward energy price	34.40	3.97	27.59	41.21
F_2 = wind PPA's forward energy price	29.43	2.26	25.54	33.31

Panel B: Regression results; regressand = $\ln[\phi^* / (1 - \phi^*)]$

Variable	OLS regression			Robust regression			Tobit regression		
	Estimate	Standard error	<i>p</i> -value	Estimate	Standard error	<i>p</i> -value	Estimate	Standard error	<i>p</i> -value
Regressand's mean	-0.2169			-0.2169			-0.3569		
Adjusted R^2	0.8974			0.9541					
Pseudo R^2							0.4830		
RMSE for the OLS and robust regressions	0.4032			0.2224					
Sigma for the Tobit regression							0.7535	0.0065	< 0.001
Intercept	1.3648	0.0102	< 0.001	1.1464	0.0040	< 0.001	1.9477	0.0151	< 0.001
$\ln(F_1 / F_2)$	-10.9900	0.0636	< 0.001	-9.3500	0.0223	< 0.001	-15.2569	0.0858	< 0.001
Marginal effect of $\ln(F_1 / F_2)$ based on the Tobit regression							-14.2213	0.0488	< 0.001
Share of observations with $\phi^* = 0$							9.55%		
Share of observations with $\phi^* = 1$							5.78%		
Own-price elasticity of solar capacity demand	-5.3365			-4.5402			-6.6690		
Own-price elasticity of wind capacity demand	-5.6534			-4.8098			-7.5523		

Note: For the OLS and robust regressions, if $\phi^* = 0.0$ (1.0), it is reset to 0.01 (0.99).

Table 7. Revised results for ϕ^* = optimal solar capacity share and B^* = minimum risk-adjusted budget based on the monthly price quotes for electricity futures downloaded on 10/11/2023

Description	F_1	F_2	ϕ^*	B^*
(1) Average forward energy prices of recently signed VRE PPAs (Bolinger et al., 2021; Wiser et al., 2021)	25	25	0.57	-4,115
(2) Average forward energy prices of the US VRE PPAs in the first quarter of 2023	50	50	0.82	57,355
(3) Forward price discounts due to aggressive bidding by VRE developers participating in a LSE's procurement auction	34.00	34.39	0.68	19,069
(4) Forward energy prices without discounts/premia under the efficient market hypothesis	50.02	47.11	0.73	55,355
(5) Forward price premia due to the reasons stated below equation (7)	66.04	59.84	0.77	91,429

Table 8. Revised regression analysis of price responsiveness based on equation (12) and the monthly price quotes for electricity futures; number of observations = 10,000 based on a full factorial design that yields all possible pairs of F_1 and F_2

Panel A: Pseudo data's summary statistics

Variable	Mean	Standard deviation	Minimum	Maximum
B^* = minimum risk adjusted budget per year	50,389	16,642	19,069	91,429
ϕ^* = optimal solar capacity share	0.67	0.31	0.00	1.00
F_1 = solar PPA's forward energy price	50.02	9.34	34.00	66.04
F_2 = wind PPA's forward energy price	47.11	7.42	34.39	59.84

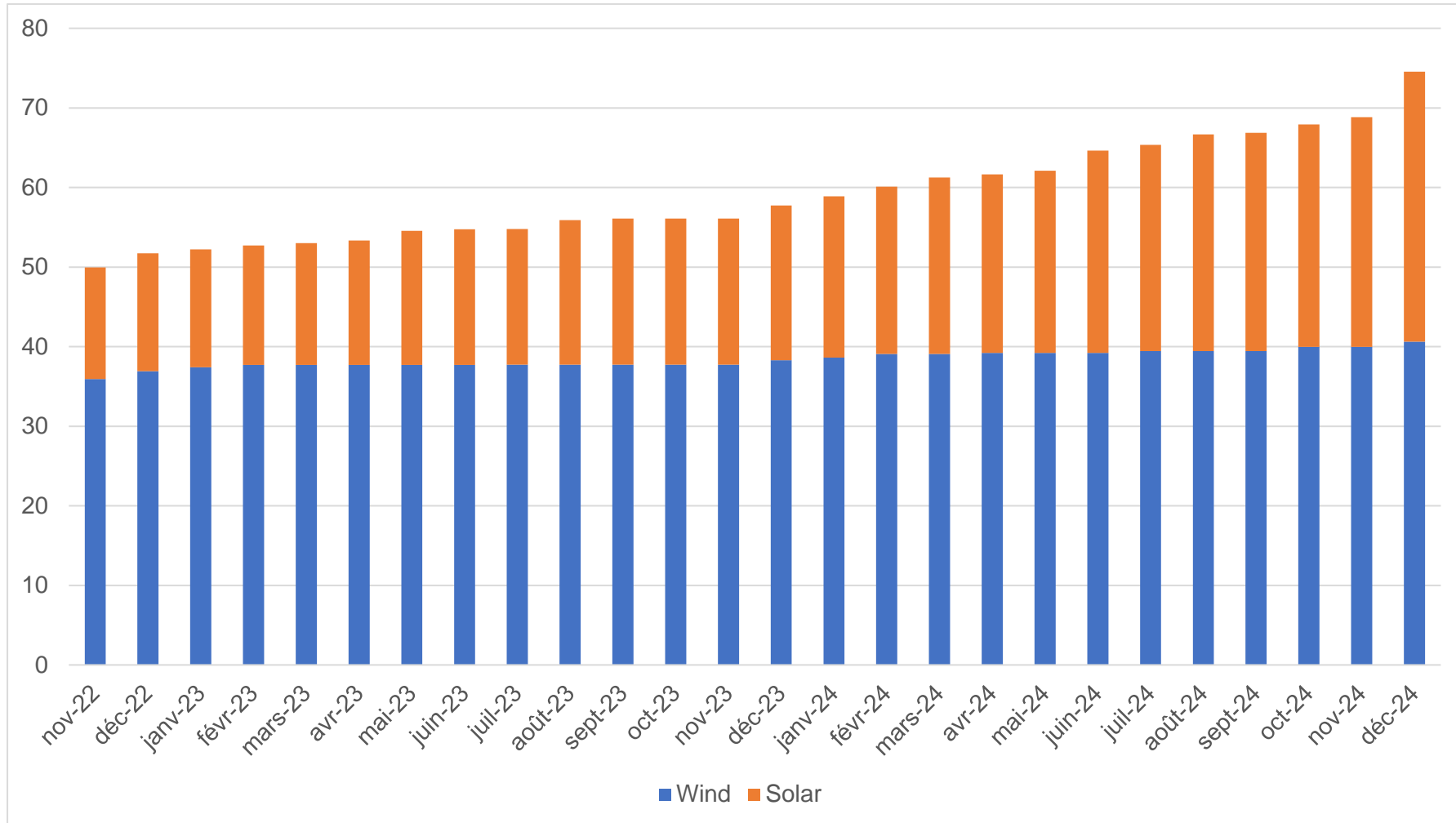
Panel B: Regression results

Variable	OLS regression			Robust regression			Tobit regression		
	Estimate	Standard error	p -value	Estimate	Standard error	p -value	Estimate	Standard error	p -value
Regressand's mean	0.6043			0.6043			1.2207		
Adjusted R^2	0.8637			0.9139					
Pseudo R^2							0.4830		
RMSE for the OLS and robust regressions	0.5068			0.3431					
Sigma for the Tobit regression							0.8869	0.0084	< 0.001
Intercept	1.6032	0.0103	< 0.001	1.4555	0.0052	< 0.001	2.1386	0.0125	< 0.001
$\ln(F_1 / F_2)$	-8.1053	0.0532	< 0.001	-7.1013	0.0260	< 0.001	-11.8362	0.0651	< 0.001
Marginal effect of $\ln(F_1 / F_2)$ based on the Tobit regression							-9.0719	0.0210	< 0.001
Share of observations with $\phi^* = 0$							6.29%		
Share of observations with $\phi^* = 1$							23.64%		
Own-price elasticity of solar capacity demand	-5.1944			-4.5510			-6.2184		
Own-price elasticity of wind capacity demand	-2.9109			-2.5503			-2.8535		

Note: For the OLS and robust regressions, if $\phi^* = 0.0$ (1.0), it is reset to 0.01 (0.99).

Figure 1. Short-term projection of Texas's solar and wind capacities based on the interconnection agreements already signed between VRE developers and ERCOT

Panel A. Monthly total GW of solar and wind capacities in the Nov-2022 to Dec-2024 period



Panel B. Monthly GW of cumulative solar and wind capacity additions in the Dec-2022 to Dec-2024 period (left axis); monthly ratios of cumulative solar capacity addition to cumulative wind capacity addition (right axis)

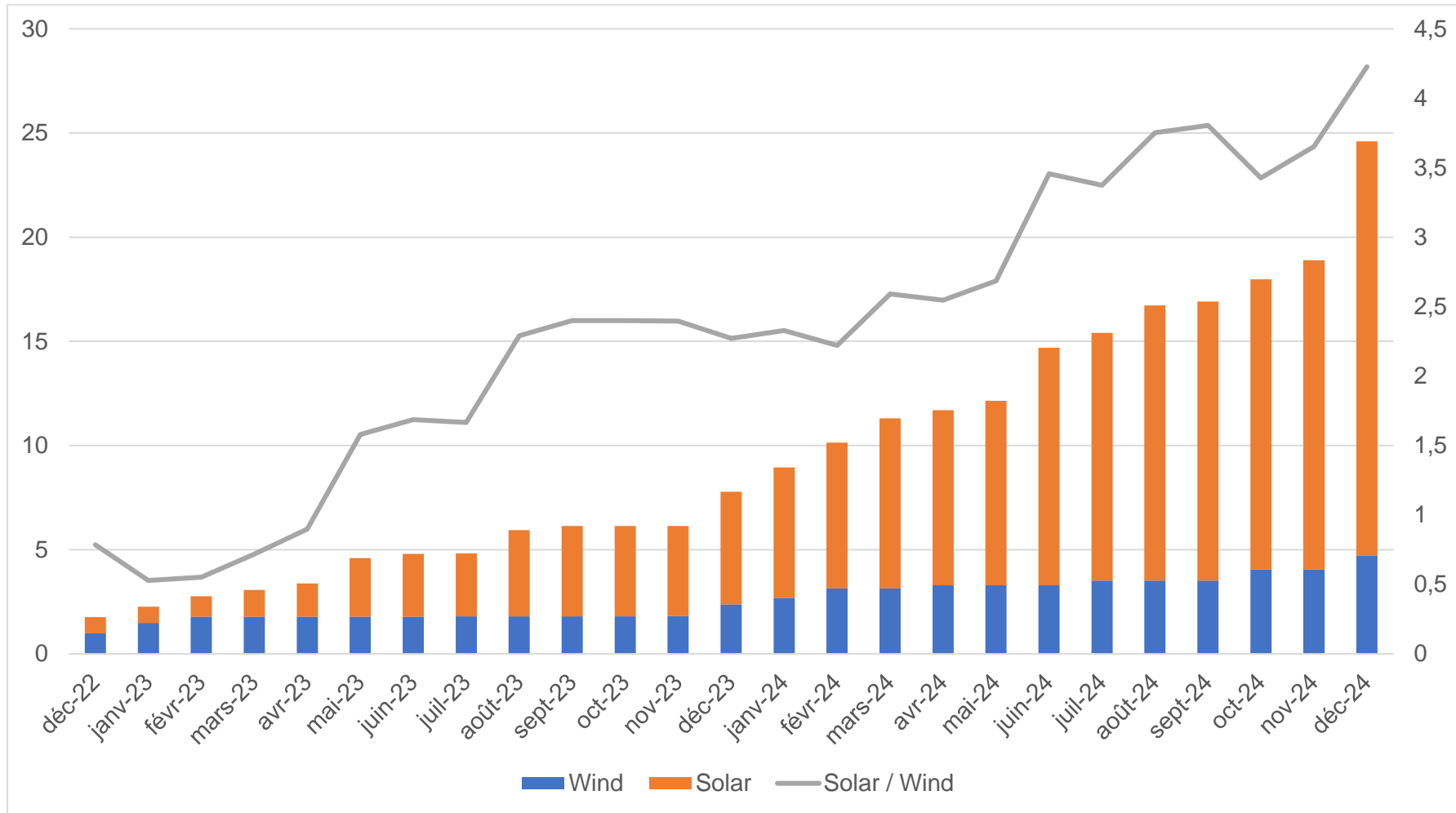


Figure 2. Monthly averages of daytime and nighttime spot energy prices (left axis) and Henry Hub natural gas prices (right axis) for the Sep-2012 to Aug-2023 period

