Time of Day Pricing and the Levelized Cost of Intermittent Power Generation

Stefan Reichelstein[*]
Graduate School of Business
Steyer-Taylor Center for Energy Policy and Finance
Stanford University

and

Anshuman Sahoo
Department of Management Science and Engineering
Steyer-Taylor Center for Energy Policy and Finance
Stanford University

April 2013

[*]Email addresses: reichelstein@stanford.edu; asahoo@stanford.edu
We would like to thank Matt Campbell of the SunPower Corporation for sharing simulation data and Wichsinee Wibulpolprasert for sharing wind generation data. We are also grateful to Richard Swanson and Michael Wara for comments and suggestions.

Abstract:

Time of Day Pricing and the Levelized Cost of Intermittent Power Generation

An important characteristic of most renewable energy sources is their intermittent pattern of electricity generation. Yet, intermittency is usually ignored in life-cycle cost calculations intended to assess the competitiveness of electric power from renewable as opposed to dispatchable energy sources, such as fossil fuels. This paper demonstrates that for intermittent renewable power sources a traditional life-cycle cost calculation should be appended by a correction factor which we term the *Co-Variation coefficient*. It captures any synergies, or complementarities, between the time-varying patterns of power generation and pricing. We estimate the Co-Variation coefficient for specific settings in the western United States. Our estimates imply that the benchmark of cost competitiveness for solar PV power is 10-15% lower than average life-cycle cost analyses have suggested. In contrast, the generation pattern of wind power exhibits complementarities with electricity pricing schedules, yielding a cost competitiveness assessment 10-15% above that suggested by traditional calculations.

Keywords: Levelized Cost of Electricity, Renewable Energy, Intermittent Electricity Generation, Solar PV, Wind Power.

1 Introduction

Renewable energy sources, in particular solar and wind power, have seen impressive growth in new installations over the past decade.[1] Yet, the cost competitiveness of these renewables remains controversial, with many analysts pointing to public subsidies in the form of tax credits, accelerated tax write-offs and clean energy portfolio standards. One factor complicating the assessment of the economic viability of renewables is their intermittency.[2] In particular, wind and solar power are well known to exhibit considerable variation in their ability to generate power. These variations typically include both time of day fluctuations and seasonal cycles.

One approach commonly employed in the energy literature to compare the cost effectiveness of alternative power sources is the so-called *Levelized Cost of Electricity* (LCOE). This life-cycle cost concept seeks to include all cost components of a power generation facility, including upfront capital expenditures, variable and fixed operating costs and applicable taxes.[3] The LCOE is calculated as the break-even price that investors would have to receive *on average* per kilowatt-hour (kWh) generated in order to cover all costs and receive an adequate return on their initial investment. In calculating this life-cycle cost figure, the vast majority of existing studies rely on average *capacity factors*, that is, the average power generated by a particular facility in any given year. For base-load natural gas power plants, for instance, this average capacity factor is typically specified in the range of 85-90% of the energy theoretically available, with the remaining 10-15% accounting for scheduled maintenance. In contrast, the patterns of direct sun exposure limit the average capacity of solar PV installations to around 20-25% of theoretical capacity.

Consider an investor who seeks to evaluate the economic attractiveness of installing solar

[1]For instance, almost 17 gigawatts (GW) of new solar photovoltaic (PV) power were installed worldwide in 2010. This addition represented a 250% increase relative to 2009 and was roughly equal to the total *cumulative* amount of solar PV power installed since the commercial inception of solar PV technology in the 1970s. Current estimates suggest the total cumulative amount of solar PV installed is close to 100GW (Alster, 2013)

[2]Baker, Fowlie, Lemoine, and Reynolds (2013) distinguish between variable and intermittent power generation, with the former referring to predictable daily and seasonal patterns and the latter to unpredictable interruptions, for example those due to cloud cover. Our use of the term intermittency is consistent with the earlier economics-based literature which includes both effects.

[3]See, for example, EPIA (2011), Campbell (2008), Campbell (2011), Werner (2011) and Reichelstein and Yorston (2012a).

panels on a rooftop. Despite the daily variations in the pattern of power generation, the traditional LCOE calculation, with reliance on the average capacity factor, will still be conceptually sound provided the investing party faces a flat rate per kWh that it would alternatively have to pay for obtaining power from the grid. However, if the investor faces a price schedule that varies by time of day and possibly also by season, the traditional LCOE calculation will generally fail to capture any synergies that arise if the solar facility generates power above its overall average predominantly at times when electricity prices are relatively high.

Earlier literature has argued that a levelized cost analysis may be "flawed" or "misleading" when applied to intermittent power sources. Borenstein (2012) provides a broad survey of cost calculations for various electricity generation technologies. Joskow (2011a, 2011b) presents several illustrative examples comparing the cost and profitability of dispatchable versus intermittent power generation facilities. For solar photovolatic (PV) power, Borenstein (2008) quantifies the synergistic effect between the pattern of electricity prices and that of power generation. His analysis suggests that the "bonus" value for electricity generated from solar power is at least 0-20% and may be as high as 30-50%. In contrast, Fripp and Wiser (2008) observe that the pattern of wind power generation implies a complementarity with the daily variation in electricity prices since wind generation tends to be highest at night, when electricity prices are relatively low. Fripp and Wiser confirm this intuition and conclude that a "penalty" factor of about 5-10% ought to be applied to the value of power generated from wind turbines.

The main point of our paper is to demonstrate that a levelized cost analysis remains appropriate for assessing the cost competitiveness of an intermittent power source, provided the figure obtained from a traditional average LCOE calculation is modified by a correction factor which we term the *Co-Variation coefficient*. As the name suggests, this coefficient captures the synergy (or complementarity) between temporal variations in electricity generation and prices across times of the day and days of the year. By construction, dispatchable energy sources, like fossil fuel-fired power plants, will have a Co-Variation coefficient of one. Conversely, the Co-Variation coefficient will also be equal to one for an intermittent power source that faces a time-invariant pricing schedule. One benefit of our approach is that existing LCOE calculations, which have ignored synergies between price variations and the intermittency of power generation, do not need to be "shelved." Instead, they should be appended by a correction factor given by the Co-Variation coefficient.

The Co-Variation coefficient is related to the work of Borenstein (2008) and Fripp and Wiser (2008). Both papers estimate an incremental percentage value attributable to temporal patterns in electricity generation and pricing. Focusing on wind power, Fripp and Wiser (2008) calculate the difference between the annual wholesale revenues implied by a hypothetical constant generation pattern and those by the actual intermittent generation pattern. Specifically, they sum the hourly products of a constant power output and time-varying wholesale prices and compare it against a corresponding value in which both prices and output generated vary over time. Borenstein (2008) estimates a similar metric for electricity from solar PV facilities. Instead of assuming a hypothetical scenario in which generation remains constant, Borenstein calculates an average wholesale price that would be revenue-neutral relative to time-varying wholesale prices. He subsequently quantifies the incremental value of overlapping temporal price and generation patterns as the difference between i) the present value corresponding to time-varying output and wholesale prices and ii) the present value corresponding to time-varying output prices and the hypothetical constant price.[4]

Our conceptual contribution in this paper is to derive a measure of synergy (complementarity) that can be embedded in a levelized-cost framework. The Co-Variation coefficient is shown to be the appropriate synergy measure insofar as the traditional levelized cost, adjusted by the Co-Variation coefficient, determines whether a particular electricity generating facility is cost competitive. In particular, the metric provides the price threshold required for investors in the facility to break even. Thus our extended levelized cost concept addresses the Joskow critique that traditional LCOE calculations are prone to neglect a substantial aspect of the economics of renewable energy sources (Joskow (2011a) and Joskow (2011b)).

By focusing on the implications of synergies or complementarities from an individual investor perspective, our paper complements work by Lamont (2008) and Baker et al. (2013). These papers derive the marginal value of intermittent capacity to the electricity network at large. Lamont argues that the long-term marginal value of intermittent generators to the electricity network is the sum of two terms: the first reflects the total energy that an intermittent generator can provide over one year, regardless of generation and pricing patterns. The second term captures the degree to which electricity generation and systemic marginal

[4]The valuation used by Borenstein also accounts for benefits from reduced line losses implied by the distributed nature of solar PV generation.

costs overlap. The marginal value derived by Baker et al. retains these two terms and adds another that accounts for the "monetized" value of emissions offset by the intermittent generator. This value is adjusted by the degree to which the intermittent generation and marginal emissions rate profiles coincide.

The ongoing discussion about the economics of renewable energy points out correctly that one undesirable consequence of intermittency is the need for back-up power in order to ensure grid stability. We emphasize that our analysis ignores this aspect even though it will become increasingly prominent as renewable energy sources provide a more substantial share of the overall electricity supplied.[5] Specifically, the addition of substantial amounts of intermittent energy sources to the electrical grid is likely to require the installation of additional back-up power to balance supply and demand on the electrical network.

As an application of our conceptual framework, we derive estimates of the cost impact of time-varying generation and pricing patterns for both solar PV and wind power. Our data pertain to facilities in the western United States. For solar power, we quantify the Co-Variation coefficient for both commercial- and utility-scale installations in northern California. Our power generation data are based on simulations for the San Francisco Bay Area from the PVWatts program developed by the National Renewable Energy Laboratory (NREL) (NREL, 2012a). The corresponding price distributions are obtained at the wholesale level from the California Independent Systems Operator (CAISO) and at the retail level from particular rate schedules (A-6 and E-20) that Pacific Gas & Electricity (PG&E) offers to commercial customers. Our wind power calculations focus on utility-scale facilities in the San Francisco Bay Area, and our generation data are based on simulations recorded in the NREL Wind Integration Dataset (NREL, 2012b).

The most significant daily Co-Variation coefficient in our calculations amounts to 1.61 for solar PV installations. The magnitude of this coefficient is largely attributable to the fact that PG&E charges its commercial customers on the A-6 pricing schedule up to 44 cents per kWh in the summer during peak afternoon hours. As one might expect, the overall yearly Co-Variation coefficient for this category of installations is substantially smaller and amounts to 1.17. Nonetheless, since $.85 = 1/1.17$, we conclude that the effect of intermittency in the context of this rate schedule is that commercial-scale solar PV facilities would be cost com-

[5] Dispatchable energy sources also require back-up power to account for unscheduled plant shutdowns. One potential advantage of renewable power in this context is its decentralized base of many relatively small generation facilities.

petitive if they were to face an average price 15% lower than that implied by a traditional LCOE calculation. To put this finding in absolute terms, a traditional life-cycle cost calculation for commercial-scale installations in San Francisco suggests an LCOE figure of 14.2 cents per kWh, based on 2012 data.[6] Our analysis concludes that new commercial-scale installations would be cost competitive if PG&E were to charge its commercial customers on average at least $.85 \cdot 14.2 = 12.1$ cents per kWh.

For utility-scale solar PV installations, we take the applicable price distribution to be wholesale prices in California. The daily variation in one-day ahead prices as posted by the CAISO is considerably smaller, in both the summer and winter seasons, than the daily variation in commercial retail rates charged by PG&E. Accordingly, we obtain a smaller Co-Variation coefficient for solar facilities of about 1.1. The intermittency of utility-scale solar PV installations implies that they are cost competitive when faced with a price distribution whose average is 10% lower than that suggested by a traditional LCOE calculation. Many industry analysts have pointed out that trackers have considerable potential to improve the economic viability of utility-scale solar installations because trackers boost the capacity factor of solar panels. While this capacity effect is uncontroversial, our analysis concludes that the value of trackers is unrelated to the cost effect attributable to intermittency. In other words, trackers have no tangible impact on the Co-Variation coefficient.

Our calculations confirm that the pattern of wind power generation exhibits a complementarity with wholesale electricity prices. Specifically, we estimate Co-Variation coefficients of 0.87 and 0.92 for wind generation sites near Livermore, CA and Benicia, CA, respectively. The intermittency of wind installations thus implies that wind facilities are competitive only when coupled with a price distribution whose average price is about 9-15% higher than that suggested by traditional life-cycle cost calculations.

The remainder of the paper is organized as follows. Section 2 presents the traditional average LCOE concept as developed in earlier studies. In Section 3, we derive the Co-Variation coefficient and demonstrate that a simple average LCOE calculation supplemented by the Co-Variation coefficient is appropriate to evaluate the cost competitiveness of intermittent power sources. We also provide sufficient conditions for a pair of price and generation distributions to exhibit synergies. Section 4 derives numerical estimates of the Co-Variation

[6] This estimate is based on the Solar PV calculator in Reichelstein and Yorston (2012b). It incorporates the tax subsidies currently available to investments in solar PV generation and consistently assumes the most favorable but realistic parameter values.

coefficient for solar PV power, and Section 5 presents a parallel analysis for wind power. We conclude in Section 6.

2 Levelized Cost of Electricity

The Levelized Cost of Electricity seeks to account for all physical assets and resources required to deliver one kilowatt-hour of electricity. Fundamentally, this concept seeks to identify a per unit break-even value that a producer would need to obtain in sales revenue in order to justify an investment in a particular power generation facility. The levelized cost of electricity must thus be compatible with present value considerations for both equity and debt investors. In "The Future of Coal" (MIT, 2007), the authors offer the following verbal definition:

"*...the levelized cost of electricity is the constant dollar electricity price that would be required over the life of the plant to cover all operating expenses, payment of debt and accrued interest on initial project expenses, and the payment of an acceptable return to investors*".

The LCOE concept is widely used by researchers, academics and government institutions to compare the cost effectiveness of alternative energy sources which differ substantially in terms of upfront investment cost and periodic operating costs. However, the formulaic implementation of this concept has been lacking in uniformity. In particular, some authors have conceptualized LCOE as the the ratio of "total lifetime cost" to "total lifetime electricity" produced (EPIA, 2011; Campbell, 2008, 2011; Werner, 2011). This is generally incompatible with the preceding verbal definition. The following derivation follows that in Reichelstein and Yorston (2012a).

For a new production facility to be built, the levelized cost of one kilowatt-hour aggregates the upfront capacity investment, the sequence of output generated by the facility over its useful life, the periodic operating costs required to deliver the output in each period and any tax related cash flows that apply to this type of facility. Since the *output price* in question should lead investors to break-even, standard corporate finance theory submits that if the project in question keeps the firm's leverage ratio (debt over total assets) constant, the appropriate discount rate is the Weighted Average Cost of Capital (WACC).[7] In reference to the above quote in the MIT study, equity holders will receive "*an acceptable return*" and debt holders will receive "*accrued interest on initial project expenses*" provided the project

[7] See, for instance, Ross, Westerfield, and Jaffe (2005).

achieves a zero Net Present Value (NPV) when evaluated at the WACC. We denote this WACC interest rate by r and the corresponding discount factor by $\gamma \equiv \frac{1}{1+r}$.

Investment in the production facility is assumed to conform to a constant returns to scale technology with the following parameters:

- SP : the construction cost (in \$ per kW),
- T : the useful life of the output generating facility (in years) and
- x_i : the capacity adjustment factor: the percentage of initial capacity that is still functional in year i.

The capacity adjustment factor reflects that in certain contexts the available output yield changes over time. For instance, the efficiency of photovoltaic solar cells has been observed to diminish over time. The corresponding decay is usually represented as a constant percentage factor ($x_i = x^{i-1}$ with $x \leq 1$) which varies with the particular technology. On the other hand, production processes requiring chemical balancing, e.g., those for semiconductors and biochemicals, frequently exhibit yield improvements over time due to learning-by-doing effects. For base-load fossil fuel power plants, the usual specification is the "one-hoss shay" asset productivity scenario, in which the facility has undiminished capacity up to date T, that is $x_i = 1$ for all $1 \leq i \leq T$, and thereafter the facility is obsolete.

In any given year of its operation, the facility is theoretically available for 365 days. However, practical capacity is only a fraction of the capacity available due to maintenance requirements and, for many renewable energy sources, the fact that the energy source is available only for a fraction of the time. Since this section seeks to develop the "traditional" LCOE concept, which ignores intertemporal variations in the capacity that is available, we first represent practical capacity simply as a fixed percentage, CF, of theoretical capacity. This specification is unproblematic for a dispatachable energy source like a fossil fuel-fired power plant. We then define the *capacity cost for one kWh* as:

$$c = \frac{SP}{365 \cdot 24 \cdot CF \cdot \sum_{i=1}^{T} x_i \cdot \gamma^i}. \tag{1}$$

One interpretation of c is that, absent any other operating costs or taxes, this capacity cost would yield the break-even value identified in the verbal definition above. For each kilowatt of initial capacity acquired at the constant per unit cost, SP, the firm expects to deliver $365 \cdot 24 \cdot CF \cdot x_t$ kWh in year t. If the average revenue per kWh were to be c, then revenue in year t would be $c \cdot 365 \cdot 24 \cdot CF \cdot x_t$, and the firm would exactly break even on its initial investment over the T-year horizon.

To complete the description of the levelized cost of electricity, let F_t denote the fixed costs incurred in operating a one kilowatt facility in year t. We assume that these fixed operating costs scale proportionally with the size of the facility. Applicable examples in this cost category include insurance, management, maintenance expenditures and property taxes. The initial capacity investment results in a stream of future fixed costs and a corresponding stream of future (expected) output levels. By taking the ratio of these, we obtain the following *time-averaged* fixed operating costs per unit of output:

$$f \equiv \frac{\sum_{i=1}^{T} F_i \cdot \gamma^i}{365 \cdot 24 \cdot CF \cdot \sum_{i=1}^{T} x_i \cdot \gamma^i}. \tag{2}$$

The final cost category recognized in the model comprises the variable costs of production. The applicable production inputs in this category include fuel, direct labor and supplies. Denoting by w_i the variable cost per kWh generated in year i, we define a "time-averaged" unit variable cost per kWh in the same manner as for the fixed operating costs:

$$w \equiv \frac{\sum_{i=1}^{T} w_i \cdot 365 \cdot 24 \cdot CF \cdot x_i \cdot \gamma^i}{365 \cdot 24 \cdot CF \cdot \sum_{i=1}^{T} x_i \cdot \gamma^i} = \frac{\sum_{i=1}^{T} w_t \cdot x_i \cdot \gamma^i}{\sum_{i=1}^{T} x_i \cdot \gamma^i}. \tag{3}$$

Corporate income taxes affect the LCOE measure through depreciation tax shields and debt tax shields, as both interest payments on debt and depreciation charges reduce the firm's taxable income. While the tax shield related to debt is already incorporated into the calculation of the WACC, the depreciation tax shield is determined jointly by the effective corporate income tax rate and the depreciation schedule that is allowed for the facility. These variables are represented as:

- α : the effective corporate income tax rate (in %),
- $\hat{T}$: the facility's useful life for tax purposes (in years), which is usually shorter than the projected economic life, i.e., $\hat{T} < T$,

- d_i : the allowable tax depreciation charge in year i, as a % of the initial acquisition cost, SP,

- δ : the investment tax credit, as a % of the initial asset value, SP[8]

For the purposes of calculating the levelized product cost, the effect of income taxes can be summarized by a *tax factor* which amounts to a "mark-up" on the unit cost of capacity, c.

$$\Delta = \frac{1 - \delta - \alpha \cdot \sum_{i=1}^{T} d_i \cdot \gamma^i}{1 - \alpha}. \tag{4}$$

The expression in (4) implicitly assumes that $d_i = 0$ for $\hat{T} < i \leq T$. If $\delta = 0$, the tax factor Δ exceeds 1 but is bounded above by $\frac{1}{1-\alpha}$. It is readily verified that Δ is increasing and convex in the tax rate α. Holding α constant, a more accelerated tax depreciation schedule tends to lower Δ closer to 1. In particular, Δ would be equal to 1 if the tax code were to allow for full expensing of the investment immediately (that is, $d_0 = 1$ and $d_i = 0$ for $i > 0$).[9]

Combining the preceding cost components, one obtains the following expression for the LCOE.

Proposition 0 *The Levelized Cost of Electricity (LCOE) is given by*

$$LCOE = w + f + c \cdot \Delta \tag{5}$$

with c, w, f *and* Δ *as given in (1) -(4).*

The next section demonstrates that the cost benchmark identified in Proposition 0 is a special case of a broader levelized cost concept that applies to settings in which both power generation and pricing are subject to inter-temporal fluctuations. In the current setting, the

[8]Under current tax rules, investments in solar PV installations are eligible for a 30% investment tax credit. If the investor takes advantage of this credit, the applicable book value for future depreciation charges is reduced to 85% of the initial investment. In our model, this would translate to a requirement that $\sum_{i=1}^{\hat{T}} d_i = .85$.

[9]For solar power installations, the current U.S. federal tax code not only allows for a 30% Investment Tax Credit, but also for a five-year accelerated depreciation schedule. The effect of these tax subsidies is to lower the tax factor in (4) from about 1.3 to about .7. Since capacity related costs are the dominant component in solar PV power, the expiration of the current federal tax breaks would cause the corresponding LCOE to increase by about 75%.

significance of the LCOE figure in (5) is that, over the life-time of the facility, investors break even on their investment if *each* unit of output sells for a price p greater than or equal to $LCOE$.

3 Intermittency and Time of Day Pricing

The production capacity available from the most common renewable power sources, that is, solar PV and wind, is subject to significant intra-day and seasonal variations. On a given day of the year, say day i, the actual capacity factor is assumed to be described by a function $CF_i(t)$, for $0 \leq t \leq 24$. As before, we denote the average capacity factor by CF_i and, without loss of generality, write $CF_i(t) = CF_i \cdot \epsilon_i(t)$.[10]

Thus, $\epsilon_i(t) \geq 0$ represents the percentage deviation at time t from the average capacity factor. Accordingly,

$$24 = \int_0^{24} \epsilon_i(t)dt. \tag{6}$$

To introduce intra-day variations in the market value of the electricity produced on day i, let $p_i(t)$ denote the price of electricity at a particular hour of that day. For a commercial power producer, this would be the wholesale price at which electricity can be sold to the grid operator. For an electricity consuming business or household, $p(t)$ represents the avoided cost of having to buy electricity from the grid. It will again be convenient to represent the distribution of prices as deviations from an average daily price, p_i. Thus we write: $p_i(t) = p_i \cdot \mu_i(t)$, with:

$$24 = \int_0^{24} \mu_i(t)\ dt. \tag{7}$$

Once electricity sales prices are no longer presumed constant, the LCOE concept developed in Section 2 requires modification to take into consideration for each day of the year the pattern of intra-day variations in both prices and generation capabilities. Intuitively, the life-cycle cost of electricity generation improves if the the intermittent energy source generates

[10]Given the function $CF_i(t)$, define CF_i by:

$$24 \cdot CF_i = \int_0^{24} CF_i(t)dt.$$

The function $\epsilon_i(t)$ is then given by the ratio $CF_i(t)/CF_i$.

its output during peak price periods. This suggests the following measure of Co-Variation between prices and kilowatt-hours generated.

Definition 1: *The Co-Variation coefficient between $CF_i(t)$ and $p_i(t)$ on day i is given by:*

$$\Gamma_i = \frac{\int_0^{24} \epsilon_i(t) \cdot \mu_i(t) dt}{24} \tag{8}$$

By construction, the Co-Variation coefficient is non-negative and would be zero only in the extreme case where the facility generates electricity at times when the price is zero. It is instructive to consider the following two "corner" cases. First, with uniform pricing, that is, $p_i(t) = p_i$, the coefficient Γ_i will always be equal to 1, regardless of the capacity pattern, $CF_i(t)$. Conversely, $\Gamma_i = 1$ whenever the power source is effectively dispatchable in the sense that $CF_i(t) \equiv CF_i$. These observations suggest that 1 is the benchmark value for an intermittent power source to exhibit *value synergies* with the time of day pricing pattern.

Since there are $365 \cdot 24 = 8,760$ hours in a year, we obtain the annual price distribution, $p(\cdot)$, defined on the range $[0, 8760]$ by "stitching together" the individual $p_i(t)$. Clearly, the mean value of $p(\cdot)$ is given by:

$$p = \frac{1}{365} \sum_{i=1}^{365} p_i.$$

In stating the following result, we refer to a power generating facility that faces the price distribution, $p(\cdot)$ with mean value p as *cost competitive* if the present value of all after-tax cash flows received or paid over the lifetime of the facility is non-negative. Finally, the aggregate or annual Co-Variation coefficient is defined as the arithmetic mean of the daily coefficients:

$$\Gamma = \frac{1}{365} \sum_{i=1}^{365} \Gamma_i.$$

Proposition 1 *The intermittent power generation facility is cost competitive if and only if:*

$$\Gamma \cdot p \geq LCOE.$$

Proposition 1 shows that a traditional LCOE analysis, which abstracts from variations in the intertemporal distribution of electricity prices, needs to be appended by the Co-Variation coefficient.[11] In particular, the cost competitiveness of a power generation facility can still

[11] The proof of Proposition 1 is provided in the Appendix.

be expressed succinctly by means of the average life-cycle cost, $LCOE$, provided this figure is scaled by Γ.

Our finding puts perspective on the critique articulated by Joskow (2011b). He provides a numerical example in which an intermittent and a dispatchable generation facilitiy are characterized by virtually the same LCOE but very different economic profitabilities (net present value of cash flows). In this example, the profitability of the intermittent energy source depends crucially on whether it generates electricity: (1) only during off-peak hours, (2) during a small number of peak hours but almost exclusively during off-peak hours and (3) only during peak hours. Adding assumptions about peak and off-peak wholesale prices, Joskow (2011b) suggests that while the dispatchable facility will generate an economic profit of \$7,680, the intermittent facility will produce economic losses of \$44,880 and \$42,380 in Scenarios (1) and (2), respectively, but an economic profit of \$86,520 in Scenario 3.[12] The sensitivity of the resulting profit figures to the pattern of generation illustrates the potential bias of unadjusted LCOE calculations in assessing the economic viability of intermittent generation facilities.

The Co-Variation coefficient introduced above explicitly accounts for generation patterns and predicts economic profitability for the intermittent power source if and only if the adjusted LCOE figure is below the average of the assumed price distribution faced by the investor. To illustrate this point, we calculate the Co-Variation coefficient for the intermittent facility in each of the three scenarios considered by Joskow. His assumptions about off-peak and peak prices and the percent of time in which the system is serving peak demand allow us to calculate $\mu(t)$.[13] Furthermore, the pattern of generation stipulated for each scenario implies a corresponding $\epsilon(t)$. We obtain Co-Variation coefficients of 0.70, 0.72 and 1.58 for the three scenarios, respectively. These coefficients, in turn, yield *adjusted* LCOE figures of \$81/MWh, \$79/MWh and \$36/MWh, respectively. Since in this example the average price faced by the investor is \$57.1/MWh, we confirm the conclusion reached by Joskow (2011b) regarding profitability: the intermittent facility is cost competitive, and therefore economically profitable, only in Scenario 3, when electricity is generated exclusively during times of

[12]The profit of the dispatchable facility is not exactly zero because Joskow assumes that the facility is offline only during off-peak periods. This implies that the dispatchable facility is actually characterized by a Co-Variation coefficient greater than 1.

[13]While Joskow (2011a) assumes a particular split between off-peak and peak hours within a year, we further apply this split for a representative day. The annual Co-Variation coefficient is agnostic as to how this split is made.

peak demand.

By construction, the Co-Variation coefficient Γ will be equal to one if either prices are uniform or the capacity factor is constant. Thus, both intermittency and time of use pricing are required in order to render a traditional LCOE analysis incomplete. We next identify sufficient conditions for the Co-Variation coefficient Γ to exceed 1. The straightforward intuition here is that the two distributions $\epsilon_i(\cdot)$ and $\mu_i(\cdot)$ must concentrate a significant portion of their respective masses on a common daily time interval.

Proposition 2 *Suppose both $\epsilon_i(\cdot)$ and $\mu_i(\cdot)$ are continuous, single-peaked functions that reach their maximum at a common time t^*, $0 \leq t^* \leq 24$. Then $\Gamma \geq 1$, provided either of the following two conditions is met:*
i) $\epsilon_i(\cdot)$ is symmetric around $t^* = 12$,
ii) both $\epsilon_i(\cdot)$ and $\mu_i(\cdot)$ are symmetric.

It is readily seen that some symmetry condition will be required beyond the condition of a common peak-time in order to conclude that $\Gamma \geq 1$. To illustrate, Γ would in fact be zero in case both $\epsilon(\cdot)$ and $\mu(\cdot)$ are rectangular distributions, such that $\epsilon(\cdot) = 2$ on the interval $[0, 12]$, while $\mu(\cdot) = 2$ on the interval $[12, 24]$.

The assumption of two single-peaked distributions that both attain their maximum at a common time t^* appears reasonably descriptive for solar PV installations, in particular in jurisdictions where the power used by afternoon air conditioning is a significant demand factor. Insofar, we would expect solar PV to exhibit a Co-Variation coefficient greater than 1. In contrast, the sufficient conditions identified in Proposition 2 do not seem to hold for wind power, an observation that is consistent with the intuition that the recognition of intermittency will cause wind power to be assessed as less cost competitive than an average cost calculation would suggest. The following sections estimate the magnitude of Γ for both of these power sources.

We conclude this section by noting that the conceptual approach developed above is readily extended to settings in which the distribution of prices, $p(\cdot)$, is expected to change across years. If the useful life of the facility is $T = 25$, the 25 annual price distributions need to be "stitched together". The overall life-cycle Co-Variation coefficient would then be obtained as the arithmetic mean of the individual yearly coefficients as identified in Proposition 1.

4 Estimating the Co-Variation Coefficient: Solar PV Power

This section derives estimates for the Co-Variation coefficient associated with both utility- and commercial-scale solar PV installations. We focus on facilities in the PG&E service territory in northern California. Though the retail rates for most industrial and commercial customers in the PG&E service territory change based on the time of day, day of the week and season, these fluctuations are not necessarily aligned with those for the wholesale price of electricity. The resulting differences in the pattern of wholesale and retail prices suggest that the Co-Variation coefficients for utility-scale and commercial-scale solar installations may differ significantly.

Our focus below is on annual Co-Variation coefficients. Using the framework in Section 3, we calculate 365 daily Co-Variation coefficients and report the arithmetic means.[14] For each day, we use simulated or actual power generation data to derive a day-specific ϵ_i(t) and either the applicable wholesale prices or retail price schedule to derive a day-specific μ_i(t) vector. While the ϵ_i(t) are the same for utility and commercial-scale installations, the μ_i(t) differ by the type of solar PV facility.

4.1 Solar PV Power Generation

To estimate solar PV Co-Variation coefficients, we rely on the NREL PVWatts calculator to simulate a year of power generation data (NREL, 2012a). We ran this simulation for a PV facility in San Francisco, CA, assuming modules with an 85% DC-to-AC derate factor. Our data provide, for each day within a year, simulated hourly power generation data. We ran the simulation twice; the first assumes fixed tilt tracking arrays and the second, 1-axis tracking arrays. The data from each simulation include 8,760 (365 days $*$ 24 hours/day) distinct simulated generation values. To determine hourly capacity factors, we assume that the instantaneous power output provided by the PVWatts data for a given hour remained constant over the entire hour.[15] Figures 1 and 2 provide example summer and winter power generation curves for fixed tilt tracking arrays. While these examples are for particular days, our derivation of the annual Co-Variation coefficient uses 365 such curves.

[14]Though we use 2012 wholesale price data, with 366 days of data, the simulated generation data we use are for a non-leap year. We consequently do not use price data from February 29, 2012.

[15]We apply this assumption to derive all of the Co-Variation coefficient estimates reported in the paper.

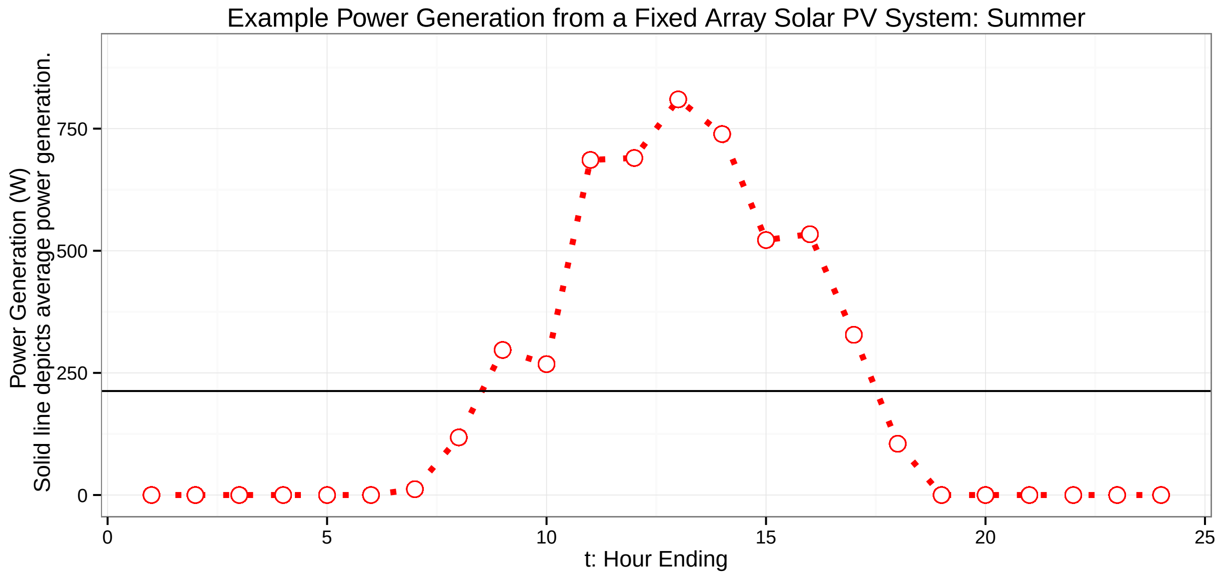

Figure 1: Example generation curve for a fixed tilt array in San Francisco, CA (summer), assuming a 1kW installation

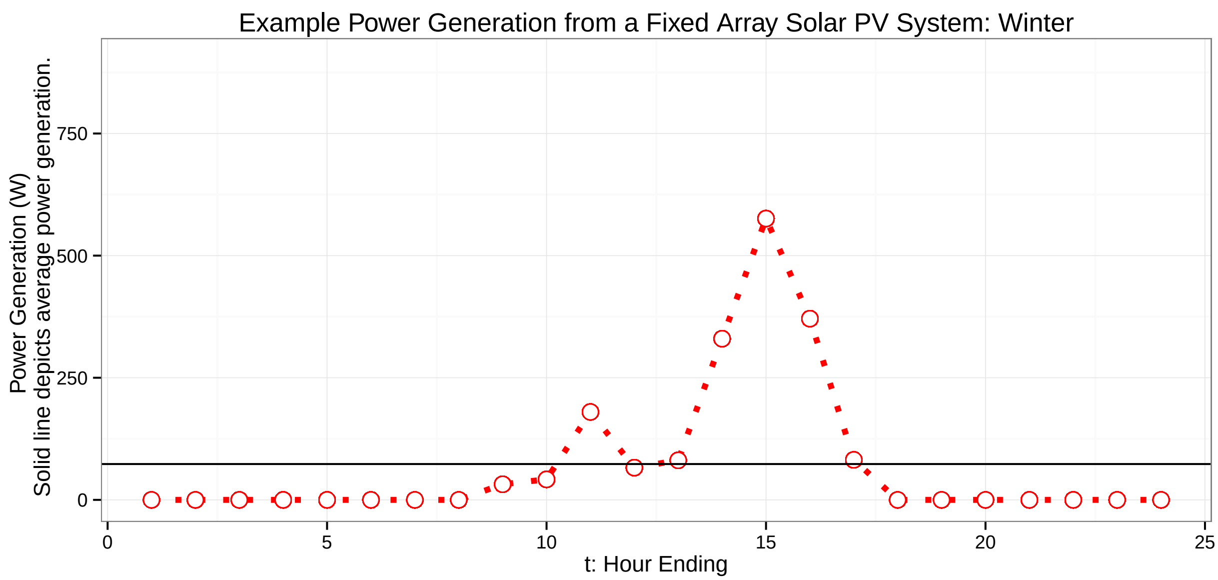

Figure 2: Example generation curve for a fixed tilt array in San Francisco, CA (winter), assuming a 1kW installation

As one would expect, power generation patterns imply that the summer capacity factor is substantially higher than the winter capacity factor. For the "representative" summer day, the capacity factor is 24%, while it is 10% for the "representative" winter day. In addition, the temporal variation in power generated relative to the mean appears substantially higher during the summer. For either daily distribution, we obtain the curve $\epsilon_i(t)$, as the ratio between $CF_i(t)$ and the mean capacity factor, CF_i, on that day.

4.2 Commercial-Scale Installations: Small Commercial Customers

Commercial-scale solar PV projects pertain primarily to rooftop solar PV generating facilities installed by commercial entities on the rooftops of their warehouses, factories or retail stores. Since the firms that install these projects can use the power generated to avoid the cost of purchasing electricity from the utility company, we use retail rate schedules to derive the price distributions $p_i(t)$ and the implied distributions $\mu_i(t)$, which measure the deviations from the mean price at a particular time.[16] The PG&E retail rates we use include the total bundled delivered price of electricity to the retail customer. Though this bundle includes charges that are unrelated to the value of electricity per se, we use it instead of generation-only prices in order to obtain an avoided-cost measure from the perspective of a potential commercial-scale investor.

Commercial electricity rates differ not only by the period of the day during which the energy is consumed, but also by the season of purchase.[17] PG&E divides the year into two seasons: the summer, which includes the period between May and October, inclusive, and the winter, which includes all other months. Regardless of season, electricity consumed during weekend and holiday days are billed at off-peak rates, so commercial customers pay the relevant season's off-peak price during all hours of these days.[18]

A commercial customer is considered to be small if its maximum power demand is below 500kW. Such customers in the PG&E service area frequently elect the A-6 electricity price schedule (PG&E, 2010a).[19] The A-6 price schedule does not include so-called demand

[16] Whenever applicable, we use secondary voltage prices. Our results would not materially differ if we were to use primary voltage prices, but transmission voltage prices within the schedules we consider have smaller absolute and relative differences between peak and part-peak and part-peak and off-peak prices than do the secondary and primary voltage price schedules. We thus expect that the Co-Variation coefficient would decrease upon substituting transmission voltage prices for secondary voltage prices.

[17] The pricing schedules used by PG&E include transitions from peak, part-peak and off-peak periods in the middle of an hour. The retail price of electricity used in our analysis for such transition hours is the average of the two prices occurring during the hour.

[18] PG&E designates eight days of the year as holidays.

[19] Small commercial customers could also elect the A-10 or E-19 rates. Those with demand grater than or equal to 499kW for three consecutive months are transferred to Schedule E-19 or E-20; the latter is

charges, and PG&E recoups the cost of serving such customers solely through energy charges. As a consequence, these energy charges are uniformly higher than those in other commercial rate schedules, like the E-20, which we examine in Section 4.3.

Figure 3 shows the time-of-use pricing schedule for commercial customers on the A-6 price schedule.[20] Most striking here is that during the peak period, prices reach a plateau level of 44.0 cents per kWh for six hours.

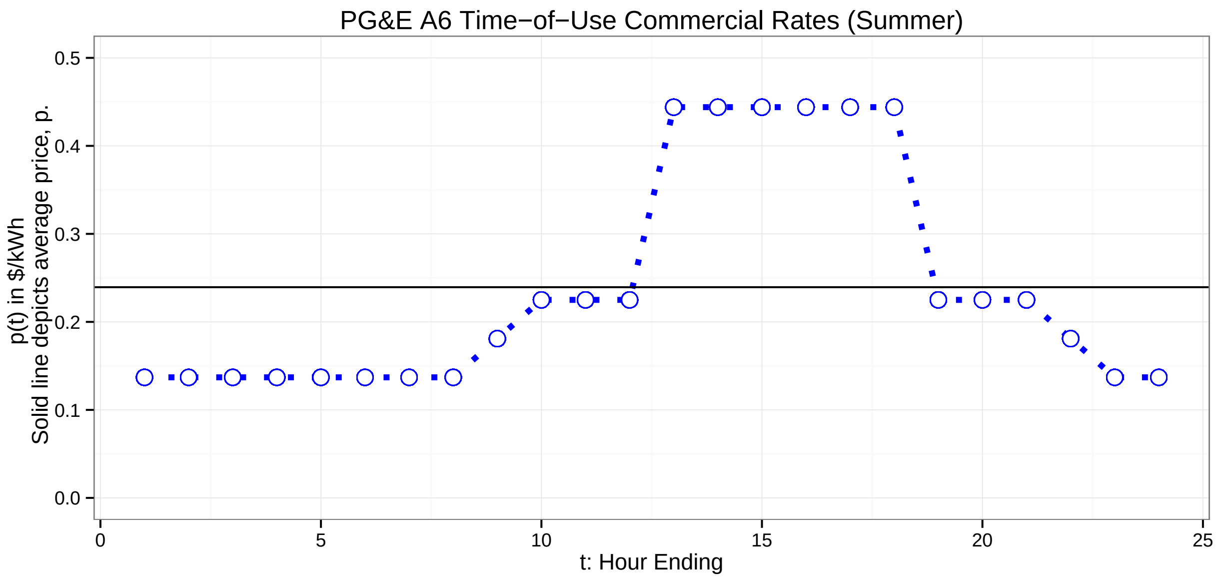

Figure 3: Example PG&E A-6 Time-of-Use price curve (summer)

Direct comparison of the distributions in Figures 1 and 3 suggests a significant correlation between the times of highest prices and the periods of highest solar generation. In fact, the Co-Variation coefficient for customers on the A-6 price schedule attains a high of 1.61 during the summer season. In contrast, the average winter Co-Variation coefficient for customers on the A-6 rate is 1.05. Figure 4 displays the corresponding winter A-6 pricing schedule. In contrast to the summer schedule, prices during the winter season remain within a much tighter range around the average price of 14.0 cents per kWh.

Combining the summer and winter data, we obtain the following yearly average Co-

generally used by customers whose maximum demand exceeds 1,000kW (PG&E, 2010b). Moreover, those with demands lower than 199kW for 12 consecutive months are eligible to elect a non-time-of-use rate schedule.

[20]Note that Figures 3 and 4 show weekday prices. On weekends and holidays, the prices are fixed at the relevant season's off-peak rate.

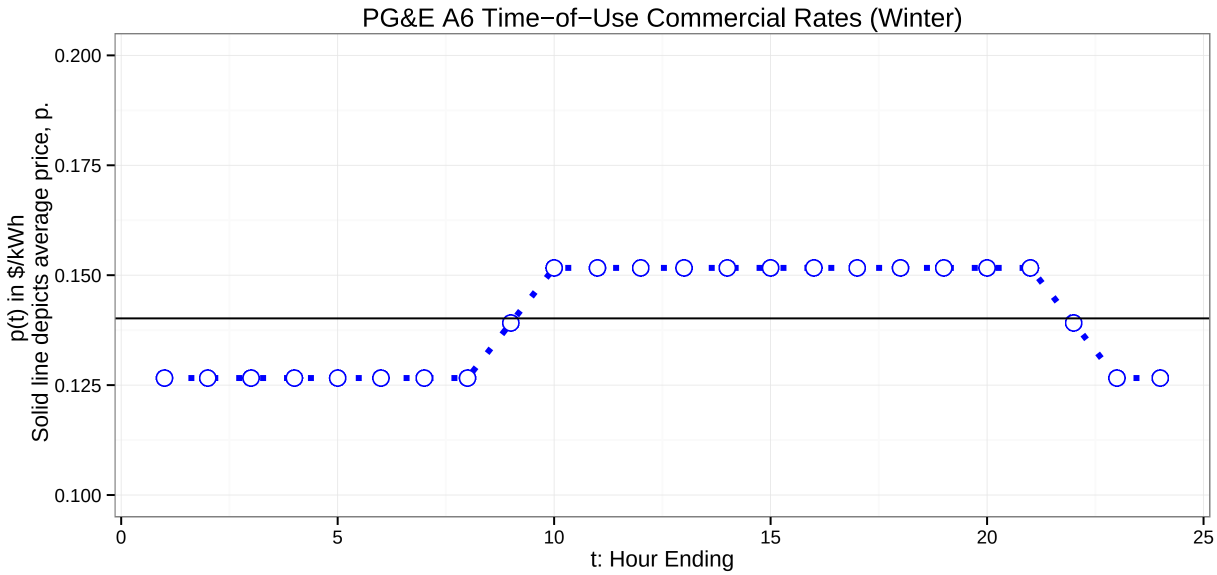

Figure 4: Example PG&E A-6 Time-of-Use price curve (winter)

Variation coefficient for customers on the A-6 rate schedule.

Proposition 3 *For customers on the A-6 electricity rate schedule, our estimate for the yearly average Co-Variation coefficient is* $\Gamma = 1.17$.

To put this finding in context, Reichelstein and Yorston (2012a) report a traditional average LCOE calculation that ignores the time-varying correlation between prices and solar power output. Assuming most favorable parameter values that were applicable in 2012, in particular for prices of solar panels, they estimate an LCOE of 12.2 cents per kWh. This estimate assumed a 17.70% DC-to-AC capacity factor, given the authors' assumption of a location with ideal solar isolation in the U.S. Since San Francisco is a less ideal location for solar PV generation, we use a San Francisco DC-to-AC capacity factor of 17.07% and obtain a traditional LCOE figure of 14.2 cents per kWh.[21] Applying the average annual Co-Variation coefficient to this estimate, our calculations suggest an adjusted LCOE of 12.1 cents per kWh. Thus we conclude that for commercial customers on the PG&E A-6 tariff, solar installations become cost competitive if prices are on average approximately 2 cents lower per kWh than suggested by a traditional life-cycle cost analysis.

[21]See Reichelstein and Yorston (2012b). We arrive at the 17.07% capacity factor by examining the ratio of simulated generation in San Francisco to that in San Diego, as provided by PVWatts.

4.3 Commercial-Scale Installations: Large Commercial Customers

We now shift attention to larger commercial customers with a maximum electricity demand of at least 1,000kW.[22] Retail electricity rates for large commercial customers often include both a fixed charge, known as the demand charge, and a variable charge, known as the energy charge.[23] The demand charge is based on the customer's maximum demand (electrical load) each month. To that end, the utility company measures the quantity of energy demanded by the customer every 15 minutes (in kilowatts), and the highest 15 minute average in a month is used as the customer's maximum demand (PG&E, 2010b).

To obtain demand charges for a particular customer, the maximum demand is measured separately for peak, part-peak and off-peak periods of the day, with the demand charge highest during peak and lowest during off-peak periods.[24] The energy charge is billed on the basis of the actual amount of power consumed, as measured by the kilowatt-hours of electricity consumed by the customer at different times of the day. The energy charge is higher during peak and part-peak periods than on the off-peak period. Other utilities have different pricing structures, and their structures may yield coefficients that differ from those reported here.

To derive the Co-Variation coefficients for large commercial customers, we use the same power generation patterns as those illustrated by Figures 1 and 2 but prices that are based on the so-called PG&E E-20 rate schedule. The average summer Co-Variation coefficient for customers on the E-20 rate is 1.16, and the maximum coefficient during the summer season is 1.32. Figure 5 illustrates the E-20 summer pricing schedule. Since the increase in prices during the peak period (1:00 p.m. through 6:00 p.m.) relative to the mean price is not as pronounced as it is in the A-6 schedule, one would expect an average summer Co-Variation coefficient lower than that for the A-6 rate.

[22]For medium-sized customers, with maximum demand between 499 and 999kW on the PG&E E-19 electricity rate schedule, we obtain essentially identical results.

[23]Though the demand charge varies with the level of energy demanded, we consider it a fixed charge since adjustments to the maximum energy load are generally made over a longer-time horizon than are changes in electricity consumption. There are other fixed charges that do not scale with the customer's size, e.g., customers are charged a daily meter charge.

[24]Within PG&E territory, the summer months include peak, part-peak and off-peak periods. While the peak and off-peak periods cover the times during which demand is highest, the part-peak period covers times of intermediate demand. Since demand in PG&E territory tends to be highest in the summer months due to cooling demand, and since the winter climate is mild across most of the utility's service territory, the winter months comprise only part-peak and off-peak periods.

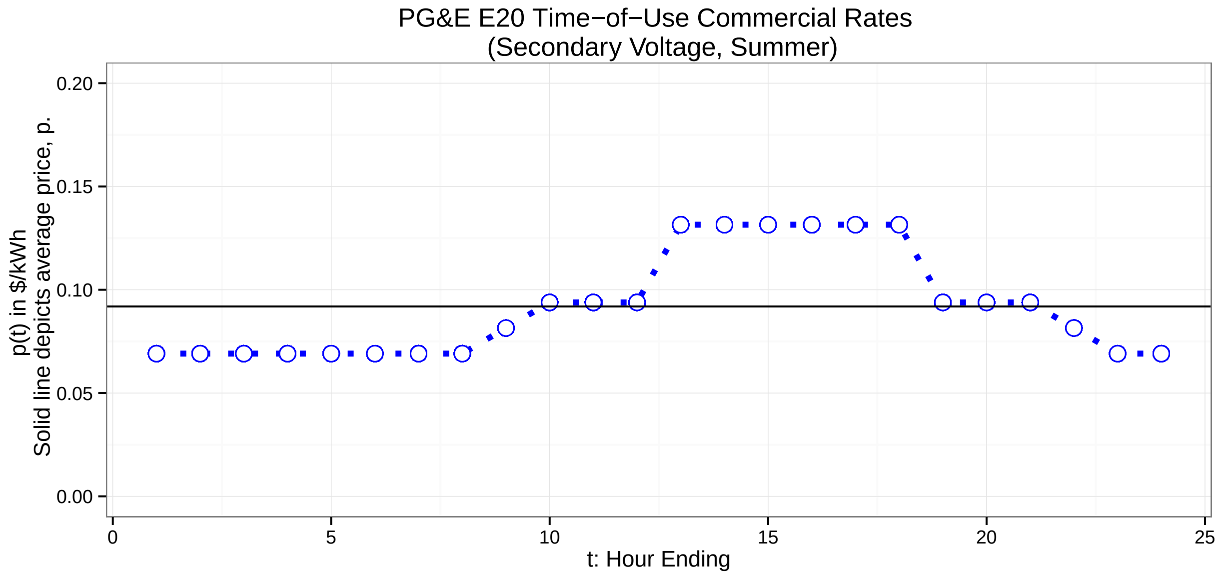

Figure 5: Example PG&E E-20 Time-of-Use price curve (summer)

Figure 6 depicts the winter E-20 price schedule. Analogous to the winter A-6 schedule, prices throughout the day remain very close to the average price of 8.0 cents per kWh, and we find an average winter coefficient of 1.07. While the absolute difference between the peak and average prices is greater for the A-6 schedule, the E-20 schedule implies a greater *relative* spread between peak and average prices and therefore a greater $\mu_i(\mathrm{t})$. The relative proximity of the average winter A-6 and E-20 Co-Variation coefficients reflects both a lower variation in prices during the winter season and a lower degree of temporal overlap between periods of high solar power generation and high prices relative to the summer season. Heating loads tend to be highest during off-peak evening and morning hours. During these hours, solar PV generation is equal or close to zero, and the actual pricing schedule therefore has little impact on the overall Co-Variation coefficient.

Combining the summer and winter data, we find the following yearly average Co-Variation coefficient for customers on the E-20 rate:

Proposition 4 *For customers on the E-20 electricity rate schedule, our estimate for the yearly average Co-Variation coefficient is* $\Gamma = 1.11$.

We emphasize that our finding in Proposition 4 should be interpreted as a lower bound on the Co-Variation coefficient, as we focus exclusively on energy charges. The existence of time-varying demand charges implies higher Co-Variation coefficients than those derived

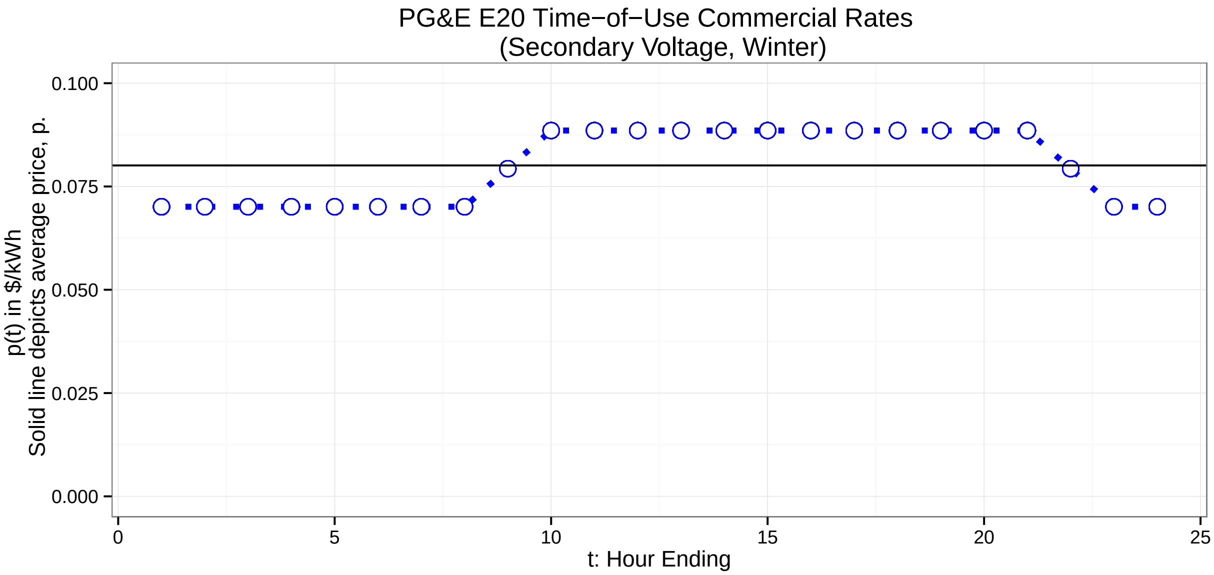

Figure 6: Example PG&E E-20 Time-of-Use price curve (winter)

here, since any reduction in demand attributable to solar PV generation during periods with higher-than-mean demand charges would increase the Co-Variation coefficient beyond the values we have calculated based only on energy charges. For the E-20 schedule, the summer demand charge is $11.68 per kW for off-peak demand but $15.72 per kW for peak demand. If a solar installation can reduce power demand preferentially at peak times, the implied Co-Variation coefficient would be higher than the one derived in Proposition 4. However, since demand reductions cannot be guaranteed without storage, we arrive at a conservative assessment by not accounting for any reduction in demand charges.

Applying the estimated Co-Variation coefficient from Proposition 4 to adjust the traditional average LCOE of 14.2 cents per kWh derived in Section 4.2 for a solar PV generation facility in San Francisco, one obtains an adjusted LCOE of 12.8 cents per kWh. Thus, for commercial customers on the E-20 tariff, the adjustment through the Co-Variation coefficient yields a cost competitiveness figure that is approximately 1.4 cents lower per kWh than that indicated by a traditional calculation.

4.4 Utility-scale Installations

Our last set of estimates for solar PV concerns the Co-Variation coefficient relevant to utility-scale solar installations. Relying on the same hourly generation data as in Sections 4.1-4.3, we now use wholesale price data from the California Independent System Operator (CAISO) Day-Ahead Market (CAISO, 2012).[25] The CAISO Day-Ahead Market is structured around three zones: the NP15, ZP26 and SP15, with the first covering electricity nodes in northern California, the middle, areas around the metropolitan Los Angeles area and the last, those in southern California. Since we consider solar PV installations in the San Francisco area, we use price data for the NP15 zone.[26]

Unlike the commercial-scale applications which have deterministic pricing structures that differ only by season, wholesale prices are determined by an hourly balancing of supply from generators with demand from customers. Thus while on weekend and holiday days, commercial retail prices are held fixed at off-peak prices, wholesale prices display a greater degree of variability. Figure 7 provides an example of locational marginal prices observed during the summer of 2012. In calculating utility-scale Co-Variation coefficients, we use 365 such daily price curves from the CAISO Day-Ahead Market.

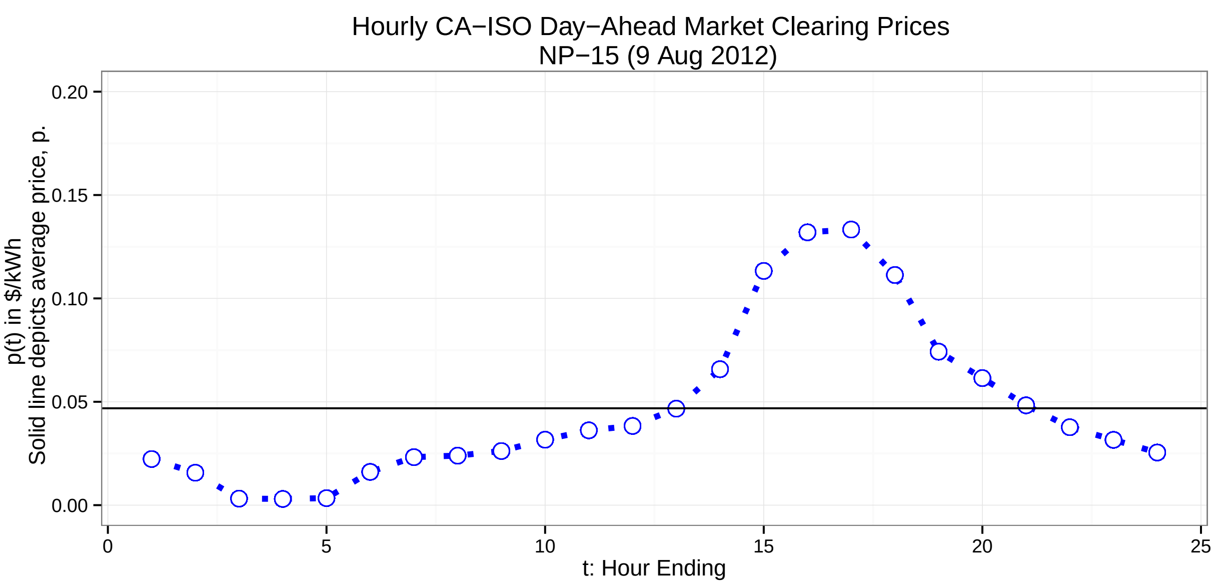

Figure 7: Example CAISO NP15 Day-Ahead Market wholesale price curve (summer)

[25]By using simulated generation data and observed wholesale price data, we are not accounting for correlations between system demand and electricity production. We expect this effect to be small, given the findings reported in Borenstein (2008). Conceptually, the correlation is imperfect since wholesale prices reflect systemic demand over a large geographical area.

[26]In particular, we use the NP15 localized marginal prices (LMP) for energy. We thus exclude the system loss and congestion effects that are separately priced and bundled with the LMP for energy to derive the total LMP.

The average summer Co-Variation coefficient for utility-scale investments is 1.17, and the highest observed coefficient is 1.43. The similarity in the coefficients reported for the summer months between utility-scale projects and commercial customers on the E-20 rate masks differences in the distribution of these coefficients. The fixed price schedule of the commercial-scale E-20 rate implies a bimodal distribution of summer Co-Variation coefficients, with one mode at 1.00, corresponding to steady off-peak prices during weekend and holiday days, and another at approximately 1.22, corresponding to the fixed weekday pricing structure. In contrast, the utility-scale summer coefficients appear to be nearly normally distributed, with a mean of 1.17 and a standard deviation of 0.07.

Figure 8 provides an example of prices observed for one day during the winter period of 2012 with an average Co-Variation coefficient of 1.05. Again, the similarity between the commercial and utility-scale coefficients masks heterogeneity in the distribution of the coefficient. While the coefficient never dips below 1.00 for the commercial rate structures, the utility-scale solar PV Co-Variation coefficient attains a minimum value of 0.87, indicating that our Co-Variation coefficient adjustment sometimes implies that the daily break-even mean price for solar PV projects is *higher* than the traditional LCOE metric suggests. However, the utility-scale Co-Variation coefficient achieves a value lower than 1 in only 39 days for the observed 2012 data; almost all of these were winter days, when μ_i(t) tended to achieve its highest values during the evening and morning hours.

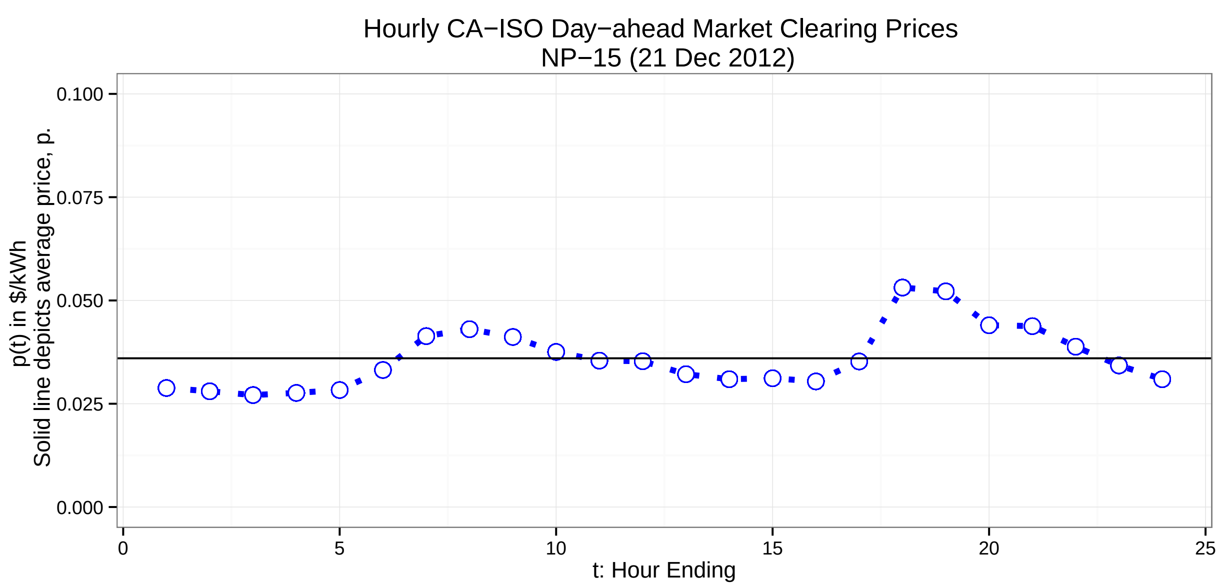

Figure 8: Example CAISO NP15 Day-Ahead Market wholesale price curve (winter)

The yearly average Co-Variation coefficient for utility-scale solar installations is estimated by combining the summer and winter data:

Proposition 5 *For utility-scale solar installations, our estimate for the yearly average Co-Variation coefficient is* $\Gamma = 1.11$.

Reichelstein and Yorston (2012a) estimate an unadjusted utility-scale LCOE of 8.0 cents per kWh, based on parameter values in 2012 for an ideal location in the southwestern U.S. This estimate relied on a 19.9% DC-to-AC capacity factor. For a San Francisco DC-to-AC capacity factor of 19.2%, the traditional LCOE figure is 8.3 cents per kWh. Applying the Co-Variation coefficient to the latter estimate, our calculations suggest an adjusted LCOE of 7.4 cents per kWh. If one compares the LCOE figures for commercial customers on either schedule and utility-scale applications, the broad-average calculations in Reichelstein and Yorston (2012b) imply a difference of 5.9 cents per kWh. Upon adjusting the LCOEs by the derived Co-Variation coefficients, the difference between commercial and utility-scale LCOEs drops to 4.7 cents per kWh for customers on the A-6 rate. Thus, we conclude that the Co-Variation coefficient deflates both the LCOE for commercial and utility-scale customers and reduces the absolute difference in LCOEs between the two solar applications.

We finally examine whether the use of traditional LCOE calculations properly reflects the value of trackers for solar PV systems. Intuitively, an average LCOE calculation for a tracking PV system may fail to capture a higher or lower co-variation between generation and energy prices relative to fixed-axis systems. Table 1 documents our estimated Co-Variation coefficients for utility-scale fixed-axis and one-axis tracking solar PV systems. We observe that the Co-Variation coefficients are essentially unchanged for the fixed-axis and one-axis tracking solar PV options.[27]

While one-axis tracking systems increase the magnitude of the generation, they do not appreciably shift patterns of generation to coincide with times of higher electricity prices. Put differently, trackers shift the distribution of generation uniformly upward but not in an incremental fashion at times of higher prices. We summarize our findings regarding the value of trackers in the following result.

[27] To test whether this finding was specific to our data, we used a separate simulation from the SunPower Corporation. These data agree with the observations in Table 1; in particular, we derive a Co-Variation coefficient of 1.09 (fixed-axis) and 1.08 (one-axis tracking).

	Γ, Utility, Fixed-Axis	Γ, Utility, One-Axis Tracking
Yearly	1.11	1.11
Minimum	0.87	0.87
Maximum	1.43	1.58
Summer	1.17	1.18
Winter	1.05	1.05

Table 1: Average yearly, summer and winter and minimum and maximum observed Co-Variation coefficients for utility-scale fixed-axis or one-axis tracking solar PV projects

Corollary to Proposition 5 *Solar PV systems with trackers have the same yearly Co-Variation coefficient as their fixed axis counterparts.*

5 Estimating the Co-Variation Coefficient: Wind Power

Wind generation facilities are usually economical only if they are of utility scale. For our application, we use simulated data for a hypothetical wind generation site between Livermore, CA and Tracy, CA and included in the NREL Western Wind Resource Dataset (NREL, 2012b).[28] The hypothetical site includes 10 3MW turbines, for a total installed capacity of 30MW, and the simulation data provide instantaneous power production in ten minute increments over the years 2004, 2005 and 2006. Our price data are the same as those used in Section 4.4. To match the six power observations within an hour to the single hourly market clearing price in the wholesale data, we aggregate data by using the minimum, average, median and maximum power data within a particular hour.

Since the implied average annual Co-Variation coefficients do not vary widely with the particular statistic used, we present results for the median. Finally, since we use simulated generation data from 2004, 2005 and 2006 but price data from 2012, we examined Co-Variation coefficients for the three years to examine the degree of variation across years. The four statistics we examined had a range of at most .02 across the three years. Below, we report results for 2005. While we cannot rule out idiosyncratic weather patterns in 2012 that would imply a materially different result, the consistency across years makes it unlikely that that our Co-Variation coefficients estimates are biased.

[28]In particular, we use data for NREL Station ID 31003.

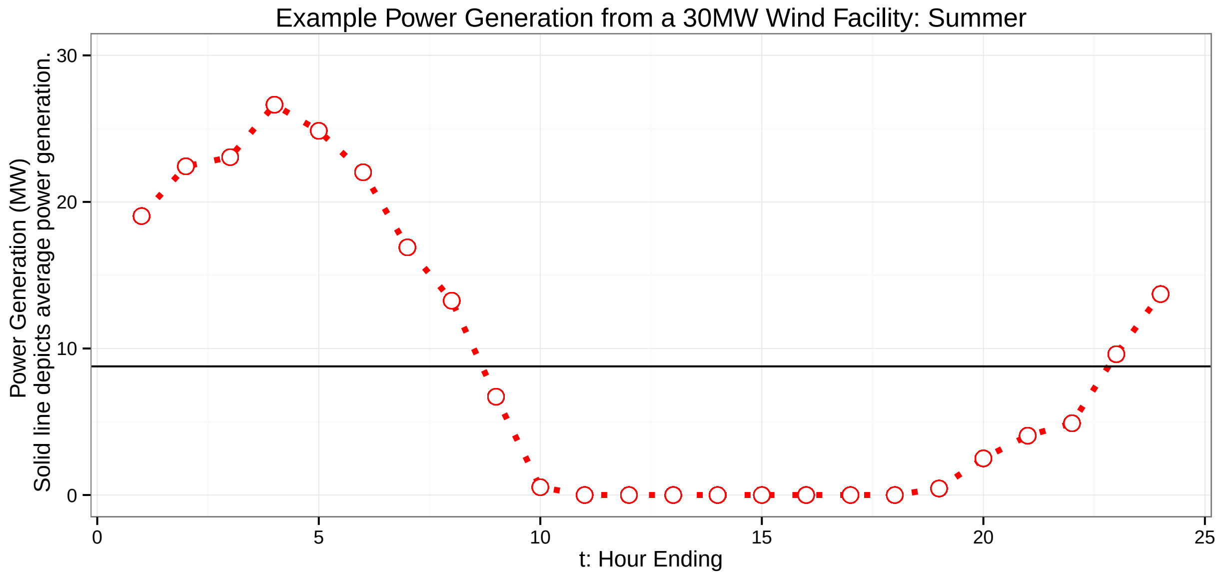

Figure 9: Example generation curve for a 30MW wind facility near Livermore, CA (summer)

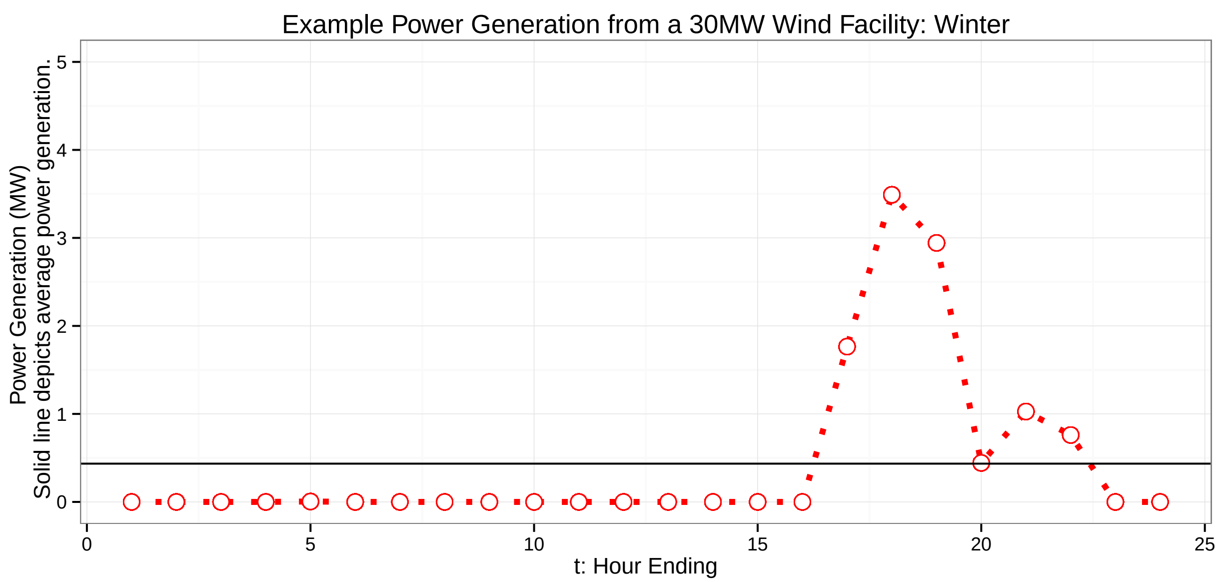

Figure 10: Example generation curve for a 30MW wind facility near Livermore, CA (winter)

Figures 9 and 10 provide examples of temporal patterns of wind power generation during the summer and winter, respectively. Wind power generation during the summer months tends to be concentrated in the evening and early morning hours, when prices are generally lowest. In contrast, winter wind power generation peaks during the day. This particular example of winter power generation highlights the calculation of the Co-Variation coefficient on the basis of the *relative* distance of the generation or price distributions from their respective mean values. While the Co-Variation coefficient for the example summer day in Figure 9 is 0.80, it is 0.95 for the example winter day. We calculate 365 daily Co-Variation coefficients and derive the relevant average.[29] Combining the summer and winter data, we find the following yearly average Co-Variation coefficient:

Proposition 6 *For the utility-scale wind installation examined, our estimate for the yearly average Co-Variation coefficient is* $\Gamma = 0.87$.

We emphasize that the point estimate of 0.87 for this particular facility may not be representative of the Co-Variation coefficients at other locations.[30] Since the pattern of generation is site-specific, Co-Variation coefficients will vary by location. To provide an example, we calculated the Co-Variation coefficient characterizing a wind facility close to Benicia, CA.[31] The Co-Variation coefficient for this facility is also lower than one, and it is approximately equal to 0.92. Thus, while an adjusted LCOE for the first facility provides a cost competitive metric 15% higher than the unadjusted version, it is only 9% higher for the Benecia facility.

6 Conclusion

While the deployment of renewable energy continues to experience steep growth, the relative cost competitiveness of these energy sources remains controversial. A traditional Levelized Cost of Electricity (LCOE) metric is generally incomplete since it only reflects average capacity factors and average electricity prices. The average LCOE thereby ignores the intermittency of renewable power and how that intermittency correlates with price fluctuations throughout the day and across seasons. The conceptual contribution of our analysis is that a traditional LCOE analysis remains valid for intermittent power sources, provided the average cost figure is supplemented by a Co-Variation coefficient that captures any synergies (or complementarities) in the daily patterns of power generation and pricing.

Applying the Co-Variation coefficient to solar PV and wind power facilities in the western U.S., we estimate that the adjusted LCOE for solar PV projects is 10% to 15% lower than

[29] Though we use 2012 wholesale price data, we do not use price data for February 29, 2012.

[30] In principle, the same caveat applies to our estimates of solar-PV Co-Variation coefficients, though the geographic dispersion is likely to be smaller for a territory like northern California.

[31] This is NREL Station ID 9667.

suggested by traditional average cost calculations, while the adjusted LCOE for wind projects is roughly 10% to 15% higher than the unadjusted version. The traditional LCOE based only on averages thus tends to undervalue solar PV projects and overvalue wind projects.

For small commercial customers in the San Francisco Bay Area, we estimate an average yearly Co-Variation coefficient of 1.17 for solar PV power generation. Upon applying this Co-Variation coefficient to unadjusted LCOE estimates, the average LCOE figure is reduced by 2 cents per kWh. For large commercial customers evaluating an investment in solar PV facilities, we estimate a yearly Co-Variation coefficient of 1.11, yielding an adjusted LCOE that is 1 cent per kWh lower than the unadjusted version.

The estimated Co-Variation coefficient for utility-scale investments is based on wholesale prices rather than commercial retail rates. Nonetheless, our estimated coefficient for utility-scale investments in solar PV match those for large commercial-scale installations. Furthermore, our simulation data suggest that trackers shift the distribution of power generation uniformly upward but not incrementally at times of higher prices. As a consequence, we conclude that the inclusion of trackers, while generally a valuable option for many utility-scale projects, does not have a measurable incremental impact on the Co-Variation coefficient relative to fixed-axis solar PV systems.

Our analysis of simulated wind facilities in the San Francisco Bay Area implies a Co-Variation coefficient of 0.87 – 0.92. While the LCOEs adjusted by the Co-Variation coefficient imply that solar facilities would be competitive with lower mean prices, they indicate that wind power projects will be competitive only with higher mean prices than suggested by traditional LCOE calculations. In the particular cases examined in our paper, the required increase in mean price is in the range of 9 – 15%.

One promising extension of our current framework would be to examine the inclusion of electricity storage systems for commercial-scale and utility-scale facilities. While currently available storage systems are likely to entail a tangible increase in the traditional LCOE, they also entail two offsetting benefits. First, storage systems could allow businesses to reduce the fixed demand charges described in Section 4. Second, power generated could be first stored and then released at times of greatest value. Finally, the inclusion of storage capabilities could limit the potential systemic costs associated with maintaining grid stability upon installing renewable energy-based electrical generation facilities.

7 Appendix

Proof of Proposition 1:

At time t in year j, the operating revenue per kilowatt of power installed is given by:

$$Rev_j(t) = x_j \cdot CF(t) \cdot p(t).$$

Here $p(t)$ is the price distribution on the range $[0, 8760]$ obtained by "stitching together" the 365 daily price distributions $p_i(t)$. Since each one of these integrates out to $24 \cdot p_i$ and the overall annual average price p was defined as:

$$p = \sum_{i=1}^{365} \frac{p_i}{365},$$

we have:

$$\int_0^{8760} p(t)dt = \sum_{i=1}^{365} 24 \cdot p_i = 365 \cdot 24 \cdot p = 8760 \cdot p. \quad (9)$$

For notational compactness, we denote $m \equiv 8760$. The overall pre-tax cash flow in year j per kW of power installed will be represented by CFL_j^o. It comprises operating revenues and operating costs:

$$CFL_j^o = x_j \int_0^m [p(t) - w_j] \cdot CF(t)dt - F_j.$$

The firm's taxable income in year j is given by:

$$I_j = CFL_j^o - SP \cdot d_j$$

The investment in one kW of power is cost competitive if, and only if, the present value of all after-tax cash flows is non-negative, that is:

$$\sum_{j=1}^{T} \quad CFL_j \cdot \gamma^j - SP(1 - \delta) \geq 0, \quad (10)$$

where CFL_j denotes the after-tax cash flow in year j:

$$CFL_j = CFL_j^o - \alpha \cdot I_j.$$

Direct substitution shows that (10) holds if and only if:

$$(1 - \alpha) \sum_{j=1}^{T} [\int_0^{365} x_j \, [p(t) - w_j] \cdot CF(t)dt - F_j] \, \gamma^j \geq \alpha \cdot \sum_{j=1}^{T} SP \cdot d_j \cdot \gamma^j + SP \, (1 - \delta). \quad (11)$$

Dividing by $(1-\alpha)$ and recalling the definition of the tax factor:

$$\Delta \equiv \frac{1-\delta-\alpha\cdot\sum_{j=1}^{T} d_j\gamma^j}{1-\alpha},$$

the inequality in (11) reduces to:

$$\sum_{j=1}^{T} x_j[\int_0^m x_j\ [p(t)-w_j]\ CF(t)-F_j]\ \gamma^j \geq SP\cdot\Delta. \tag{12}$$

In direct analogy to the definition of the annual price distribution $p(\cdot)$, we define $CF(\cdot)$ on the interval $[0,m]$ by "stitching together" the daily $CF_i(t)$. Recalling that $p(t)\equiv p\cdot\epsilon(t)$ and $CF(t)\equiv CF\cdot\mu(t)$, it follows that:

$$\int_0^m \epsilon(t)\ dt = \int_0^m \mu(t)\ dt = m,$$

Thus inequality (12) holds provided

$$p\cdot\int_0^m \epsilon(t)\cdot\mu(t)dt \geq \frac{\sum_{j=1}^{T} x_j\cdot\gamma^j\cdot m\cdot w_j\cdot CF+\sum_{j=1}^{T}\gamma^j\cdot F_j+SP\cdot\Delta}{CF\cdot\sum_{j=1}^{T} x_j\cdot\gamma^j}. \tag{13}$$

Recalling the definition of the daily Co-Variation coefficients Γ_i, the left-hand side of (13) is equal to:

$$p\cdot\sum_{i=1}^{365} 24\cdot\Gamma_i.$$

The definitions of the time-averaged unit variable cost, w, the time-averaged unit fixed cost, f, and the capacity cost, c, in Section 2, yield that the right hand side of (13) reduces to:

$$m\cdot(w+f+c\cdot\Delta)\equiv m\cdot LCOE.$$

The final step is to recognize that because $365\cdot\Gamma\equiv\sum_{i=1}^{365}\Gamma_i$, inequality (13) is satisfied if and only if:

$$p\cdot\Gamma\geq LCOE. \tag{14}$$

■

Proof of Proposition 2:

Since both $\mu_i(\cdot)$ and $\epsilon_i(\cdot)$ integrate out to 24 on the interval $[0, 24]$, the Co-Variation coefficient Γ_i is greater than or equal to one whenever:

$$\int_0^{24} \mu_i(t)[\epsilon_i(t) - 1]dt \geq 0. \tag{15}$$

For notational convenience, we henceforth drop the index i. Let t^* denote the common point in time at which both $\epsilon(\cdot)$ and $\mu(\cdot)$ reach their peak. Furthermore, let t_1 and t_2 denote two points in time such that $t_1 < t^* < t_2$ and

$$\epsilon(t_1) = \epsilon(t_2) = 1.$$

The integral in (15) can be split into four regions of integration corresponding to the intervals $[0, t_1]$, $[t_1, t^*]$, $[t^*, t_2]$ and $[t_2, 24]$, respectively. We denote the respective integrals by S_1, S_2, S_3 and S_4. Thus

$$\int_0^{24} \mu(t)[\epsilon(t) - 1]dt \equiv S_1 + S_2 + S_3 + S_4.$$

Since $\epsilon(t) < 1$ on $[0, t_1]$ and $\mu(t)$ is increasing on $[0, t^*]$, we have:

$$S_1 \geq \mu(t_1) \cdot \int_0^{t_1} [\epsilon(t) - 1]dt.$$

Also

$$S_2 \geq \mu(t_1) \cdot \int_{t_1}^{t^*} [\epsilon(t) - 1]dt,$$

since $\epsilon(t) \geq 1$ on $[t_1, t^*]$. The fact that $\mu(\cdot)$ is decreasing on $[t^*, 24]$ yields the inequalities:

$$S_3 \geq \mu(t_2) \cdot \int_{t^*}^{t_2} [\epsilon(t) - 1]dt$$

and

$$S_4 \geq \mu(t_2) \cdot \int_{t_2}^{24} [\epsilon(t) - 1]dt,$$

since $\epsilon(t) \leq 1$ on $[t^*, t_2]$.

If $\epsilon(t)$ is symmetric around $t^* = 12$, we conclude that:

$$\int_0^{12} [\epsilon(t) - 1]dt = \int_{12}^{24} [\epsilon(t) - 1]dt = 0$$

and therefore $S_1 + S_2 + S_3 + S_4 \geq 0$. On the other hand, if both $\epsilon(\cdot)$ and $\mu(\cdot)$ are symmetric around the common point t^*, then $\mu(t_1) = \mu(t_2)$ and therefore:

$$S_1 + S_2 + S_3 + S_4 \geq \mu(t_1) \cdot \int_0^{24} [\epsilon(t) - 1] dt = 0.$$

■

References

Alster, N. (2013), "Why Solar Power Stocks Are Still Earthbound," The New York Times.

Baker, E., M. Fowlie, D. Lemoine, and S. Reynolds (2013), "The Economics of Solar Electricity," *Annual Review of Resource Economics*, 5, Submitted.

Borenstein, S. (2008), "The Market Value and Cost of Solar Photovoltaic Electricity Production," CSEM WP 176.

Borenstein, S. (2012), "The Private and Public Economics of Renewable Electricity Generation," *Journal of Economic Perspectives*, 26(1), 67 – 92.

CAISO (2012), "Open Access Same-time Information System (OASIS)," http://oasis.caiso.com/.

Campbell, M. (2008), "The Drivers of the Levelized Cost of Electricity for Utility-Scale Photovoltaics," White Paper: SunPower Corporation.

Campbell, M. (2011), "Charting the Progress of PV Power Plant Energy Generating Cots to Unsubsidized Levels, Introducing the PV-LCOE Framework," in: *Proceedings of the 26th European Photovoltaic Solar Energy Conference, Hamburg (Germany)*, pp. 4409 – 4419.

EPIA (2011), "Solar Photovoltaics Competing in the Energy Sector – On the Road to Competitiveness," `http://www.epia.org/news/publications/`.

Fripp, M., and R. Wiser (2008), "Effects of Temporal Wind Patterns on the Value of Wind-Generated Electricity in California and the Northwest," *IEEE Transactions on Power Systems*, 23(2), 477 – 485.

Joskow, P. (2011a), "Comparing the Costs of Intermittent and Dispatchable Electricity Generating Technologies," Mimeo, MIT.

Joskow, P. (2011b), "Comparing the Costs of Intermittent and Dispatchable Electricity Generating Technologies," *American Economic Review Papers and Proceedings*, 100(3), 238 – 241.

Lamont, A. (2008), "Assessing the long-term system value of intermittent electric generation technologies," *Energy Economics*, 30, 1208 – 1231.

MIT (2007), "The Future of Coal," http://web.mit.edu/coal.

NREL (2012a), "PVWatts version 1," http://rredc.nrel.gov/solar/calculators/PVWATTS/version1/.

NREL (2012b), "Wind Integration Datasets," http://www.nrel.gov/electricity/transmission/wind_integration_dataset.html.

PG&E (2010a), "Electric Schedule A-6," http://www.pge.com/tariffs/tm2/pdf/ELEC_SCHEDS_A-6.pdf.

PG&E (2010b), "Electric Schedule E-20," http://www.pge.com/tariffs/tm2/pdf/ELEC_SCHEDS_E-20.pdf.

Reichelstein, S., and M. Yorston (2012a), "The Prospects for Cost Competitive Solar PV Power," *Energy Policy*.

Reichelstein, S., and M. Yorston (2012b), "Solar-LCOE Calculator," http://tinyurl.com/92ban99.

Ross, S., R. Westerfield, and J. Jaffe (2005), *Corporate Finance*, McGrawHill Publishers, New York, N.Y.

Werner, T. (2011), "Solar Power and Your Future," Presentation at the Stanford Graduate School of Business.