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# Maximizing MWh: A Statistical Analysis of the Performance of Utility-Scale Photovoltaic Projects in the United States

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## Disclaimer

## Abstract

This paper presents the first known use of multi-variate regression techniques to statistically explore empirical variation in utility-scale PV project performance across the United States. Among a sample of 128 utility-scale PV projects totaling 3,201 $MW_{AC}$, net capacity factors in 2014 varied by more than a factor of two. Regression models developed for this analysis find that just three highly significant independent variables – the level of global horizontal irradiance (GHI), the use of single-axis tracking, and the inverter loading ratio (ILR) – can explain 92% of this project-level variation (with GHI alone able to explain 71.6%). That said, adding a fourth independent variable (commercial operation year) and three interactive variables (tracking x GHI, tracking x ILR, GHI x ILR) improves the model further and reveals interesting relationships between these independent variables (e.g., the performance benefit of tracking increases with a higher GHI but diminishes with a higher ILR). Taken together, the empirical data and statistical modeling results presented in this paper can provide a useful indication of the level of performance that solar project developers and investors can expect from various project configurations in different regions of the United States. Moreover, the tight relationship between fitted and actual capacity factors should instill confidence among investors that the utility-scale projects in this sample have largely performed as predicted by our models, with no significant outliers to date. If economically warranted, future increases in capacity factors could potentially arise from greater use of dual-axis tracking, even higher ILRs, and/or solar concentrators.

## 1. Introduction

The installed cost of photovoltaic ("PV") projects in the United States has declined significantly in recent years, both at the distributed [1,2,3] and utility-scale levels [3,4,5]. Reflecting in part this decline in costs, the prices at which utility-scale PV projects have been selling their output through long-term power purchase agreements ("PPAs") have also fallen to all-time lows, below $50/MWh on a levelized basis in some cases [4,5].[1]

As a result, utility-scale PV deployment has been booming [3,5]. Just five years after the first truly "utility-scale" project – defined here as any ground-mounted project with a capacity that is larger than 5 $MW_{AC}$ – was built in the United States in 2007, the utility-scale sector became the largest segment of the overall PV market (ahead of both residential and commercial/industrial capacity) in 2012, and has held that distinction ever since. There were 9,744 $MW_{DC}$ of utility-scale PV operating in the United States at the end of 2014, nearly double the 5,087 $MW_{DC}$ of commercial/industrial and nearly triple the 3,486 $MW_{DC}$ of residential PV capacity [3]. In addition, each MW of utility-scale PV tends to generate more MWh per year than each MW of commercial/industrial or residential PV [6,7], as the latter must often contend with sub-optimal roof orientation and/or partial shading, and seldom make use of tracking devices. As a result, utility-scale PV's market-leading position is even greater in energy terms than in capacity terms [7].[2]

But the market is still young – e.g., 40% of the 9,744 $MW_{DC}$ of utility-scale PV operating in the United States at the end of 2014 came online that same year [3] – and whether or not these utility-scale projects ultimately turn out to be profitable, particularly at such low PPA prices [4,5], depends in large part on how well they perform over time. Given that substantially all costs born by utility-scale PV projects are fixed in nature (the vast majority of which are tied to initial construction of the project), the number of MWh over which those fixed costs can be amortized is a key determinant of utility-scale PV's levelized cost of energy. Understanding how existing projects have performed and what has driven variations in performance is, therefore, paramount to understanding the likely profitability of the utility-scale PV sector, which, in turn, directly impacts the sector's ability to attract the large amounts of investment capital needed to fund continued deployment at levels required to progress towards national policy goals like those of the Clean Power Plan. Moreover, the importance of project performance will only increase as the federal investment tax credit (ITC) is gradually phased down from its current 30% to 26%, 22%, and ultimately 10% in future years, leaving a greater proportion of each project's overall post-tax profit dependent on revenue tied to the number of MWh generated.

[1] These levelized prices reflect the receipt of federal tax benefits, including the 30% federal investment tax credit and accelerated tax depreciation, as well as any state-level incentives that are available, and would be higher absent these incentives.
[2] This statement generally holds true even after accounting for losses incurred by transmitting often-remote utility-scale solar generation over long distances to load. Estimates of transmission losses vary, but are generally less than 10%, and are often in the low-to-mid single digits [8,9]. For example, a recent review of utility-scale PV projects serving California load estimates transmission losses in the range of 0%-3.9%, with the upper end of the range representing projects that are located out of state [10].

Against this backdrop, this paper presents selected results from a multi-variable regression analysis of the drivers of utility-scale PV project performance, as measured empirically by net AC capacity factor in 2014 ("NCF"). The analysis is based on a sample of 128 utility-scale PV projects totaling 3,201 $MW_{AC}$ that achieved commercial operation in 18 different states over the seven-year period from 2007-2013, and that were operating throughout the entirety of 2014.[3] This sample represents essentially the entire universe of utility-scale projects that were operating in the United States at the end of 2013 [5].[4] Previous related work calculated empirical project-level NCFs from this same sample and found that they varied by more than a factor of two [5], but did not statistically evaluate the drivers of this significant variability. Other earlier work analyzed some of the predictors of PV project capacity factors in the United States, but through simulation rather than examination of empirical data [11]. In contrast, this paper presents the first known use of multi-variate regression techniques to statistically explore empirical variation in utility-scale PV project performance across the United States.

This paper proceeds as follows. Section 2 defines and characterizes the dependent variable – i.e., net AC capacity factor in 2014 (i.e., NCF) – as well as a number of independent variables that potentially influence the dependent variable, within the context of the project sample.[5] Section 3 specifies the regression model and then presents and discusses results. Section 4 concludes.

## 2. Characterization of Dependent and Independent Variables

### *2.1 The Dependent Variable: Project-Level Capacity Factors in 2014*

The purpose of our regression analysis is to examine potential drivers of the observed variation in the performance of utility-scale PV projects. In order to normalize and compare performance across all 128 projects in our sample, we rely on each project's capacity factor as the dependent variable in our regression model. The capacity factor is a measure of the actual generation from a project over the course of one or more years expressed as a percentage of the maximum possible generation from that project if it were operating at full capacity at all hours (including at night) during that same single- or multi-year period.[6] Although many projects in our sample have been operational for multiple years, thereby potentially enabling us to analyze *cumulative* capacity factors that are calculated over as many full operational years as are available for each project, we instead chose to focus exclusively on capacity factors in a single year, 2014, for three reasons:

1) ***The bulk of our project sample is very young.*** Although there are two projects in the sample that date back to 2007 (and hence have been operational for seven full years, from 2008-

[3] None of these 128 projects includes any type of storage capacity; rather, all generation net of the project's own consumption is delivered to the grid in real time.
[4] Note that the definition of "utility-scale" used in this paper – i.e., any ground-mounted project larger than 5 $MW_{AC}$ – varies somewhat from how others [3,7] define it.
[5] Unless otherwise noted, the project-level data behind these dependent and independent variables come from [5].
[6] The formula is: Net Generation ($MWh_{AC}$) over Single- or Multi-Year Period / [Project Capacity ($MW_{AC}$) * Number of Hours in that Same Single- or Multi-Year Period]. For variable, weather-dependent generation technologies like solar and wind that can exhibit strong seasonal generation profiles, capacity factors should only be measured over full-year increments.

2014, over the period of study), only 10% of the total projects in the sample and 7% of the total capacity were built in the four years from 2007-2010. Conversely, 90% of all projects in the sample, and 93% of all capacity, were built in the three years from 2011-2013, with 2013 alone accounting for 37% of all projects and 52% of all capacity in the sample (Table 1). With the bulk of our sample having been built in either 2013 or 2012, it seemed more appropriate to focus on performance in one or more recent years than to include performance from as far back as 2008 in some cases, as would be the case if working with cumulative capacity factors.

**Table 1. Project Sample by Commercial Operation Year**

| COD Year | Projects in Sample | Capacity in Sample ($MW_{AC}$) |
|---|---|---|
| 2007 | 2 | 19 |
| 2008 | 1 | 10 |
| 2009 | 3 | 54 |
| 2010 | 7 | 144 |
| 2011 | 32 | 464 |
| 2012 | 36 | 834 |
| 2013 | 47 | 1,676 |
| **Total** | **128** | **3,201** |

2) ***Data availability favors a focus on 2014.*** We have access to high-quality, site-specific insolation data for 2014,[7] but not for earlier years. Even under normal atmospheric conditions, the strength of the solar resource can vary by up to 10% or more from year to year, and these inter-year variations are not necessarily consistent across sites – i.e., insolation may increase in some regions but decrease in others [12,13]. Without knowing how insolation has varied from year-to-year at each project site, these annual deviations from the long-term norm could confound an analysis of *cumulative* capacity factors.[8]

3) ***Focusing on 2014 allows us to isolate the potential impact of time.*** Focusing on performance in a single year – and specifically the most recent year possible – enables us to better isolate the potential impact of time (manifested here in the year in which commercial operation is achieved) within the regression model. For example, assuming we have adequately controlled for all other influences, comparing how older and newer projects

[7] Vaisala – a prominent solar and wind resource consultancy (www.vaisala.com) – graciously furnished us with site-specific 2014 insolation estimates for each project in our sample. These estimates are based on project coordinates that we provided, in conjunction with Vaisala's publication of resource deviations from long-term norms in 2014 [13]. Without Vaisala's data, we may have instead had to rely on publicly available government data on long-term average annual insolation over the period from 1998-2009 – a period that does not match the 2008-2014 performance period of the oldest projects in our sample, and does not overlap at all with the 2012-2014 performance period of 90% of our sample. This mismatch in measurement periods could have potentially biased the analysis due to the inter-year variation in the solar resource noted above.

[8] For example, even ignoring any site-specific differences, if 2014 was generally a strong insolation year compared to 2013, then projects built in 2013 (which were operational for a full year only in 2014) would likely have higher *cumulative* capacity factors than projects built in 2012 (which were operational for all of 2013 and 2014) for this reason alone. Focusing instead on capacity factors in a single year – 2014 in this case – enables us to somewhat control for these inter-year variations in the strength of the solar resource. That said, focusing exclusively on 2014 also means that the *absolute* capacity factors discussed in this paper may not be representative over longer terms if 2014 was not a representative year in terms of the strength of the solar resource.

performed in 2014 might help to shed light on empirical module degradation rates over time. This time variable becomes less-intuitive and less-meaningful if analyzing cumulative capacity factors measured over multiple years.

Thus, refining the formula presented earlier in footnote 6, we focus in this paper on capacity factors in calendar year 2014, using the following formula:

$$Net\ Capacity\ Factor\ in\ 2014\ (\text{"}NCF\text{"}) = \frac{Net\ Generation\ (MWh_{AC})\ in\ 2014}{Project\ Capacity\ (MW_{AC})\ \times\ 8{,}760\ Hours\ in\ 2014}$$

Note that we express capacity factors in *net*, rather than *gross*, terms (i.e., they represent the output of each project to the grid, net of its own consumption). They are also expressed in AC terms (i.e., using the $MW_{AC}$ rather than $MW_{DC}$ capacity rating of each project), which results in higher capacity factors than if expressed in DC terms (assuming, as is typically the case, that a project's AC capacity rating is less than its DC capacity rating)[9] but allows for direct comparison with the capacity factors of other generation sources (e.g., wind energy or conventional energy), which are also calculated and expressed in AC terms.

### *2.2 Possible Drivers of Project-Level Capacity Factors in 2014*

A utility-scale PV project's capacity factor can be influenced by a number of independent variables, as described below.

***Strength of the solar resource:*** The amount of solar generation is, of course, directly correlated with the amount of solar energy, or insolation, reaching the PV array.[10] For PV projects, global horizontal irradiance ("GHI"), which measures both the direct and diffuse sunlight reaching the array, is the most appropriate measure of insolation.[11] As mentioned earlier, Vaisala provided us with average annual GHI estimates in 2014 for each site in our sample, which range from 3.73-6.02 kWh/m$^2$/day with a median of 5.39 kWh/m$^2$/day (Table 2) and a mean of 5.08 kWh/m$^2$/day (Table 3). Not surprisingly, the majority of the projects in our sample are located in the southwestern United States, where the solar resource is the strongest (Table 3).[12]

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[9] For example, a project with a 30% capacity factor in AC terms would have a 25% capacity factor in DC terms if, as is typical, the DC capacity of the array were 20% greater than the AC capacity of the inverter.

[10] Irradiance (W/m$^2$) measures the *power* of the sun reaching a square meter of the earth's surface at any given time, while insolation (kWh/m$^2$/day) measures the amount of solar *energy* reaching that same surface over the course of a day. One can derive average insolation – the variable used in this analysis – from average irradiance by multiplying the latter by 0.024.

[11] Another measure of insolation, direct normal irradiance ("DNI"), measures only the direct radiation reaching the array. DNI is more suitable for concentrating solar projects, including concentrating photovoltaics (none of which are in our sample) and concentrating solar thermal (which is outside the scope of this PV-focused analysis), as well as perhaps PV projects that employ dual-axis tracking (none of which are in our sample).

[12] For example, 83% of the capacity and 66% of the projects in our sample reside within the five states (AZ, CA, NV, CO, and NM) that have the highest mean capacity factors and 2014 GHI in Table 3. California alone accounts for 49% of the capacity and 32% of the projects in the sample.

**Table 2. Sample Descriptive Statistics**

| | Project Capacity ($MW_{AC}$) | 2014 Net Capacity Factor | 2014 GHI ($kWh/m^2/day$) | ILR ($MW_{DC}/MW_{AC}$) |
|---|---|---|---|---|
| Minimum | 5.2 | 14.8% | 3.73 | 1.05 |
| 10th percentile | 7.6 | 18.4% | 3.84 | 1.11 |
| 25th percentile | 10.0 | 20.7% | 4.65 | 1.17 |
| Median | 15.0 | 25.7% | 5.39 | 1.24 |
| 75th percentile | 20.0 | 29.9% | 5.61 | 1.28 |
| 90th percentile | 38.5 | 31.8% | 5.81 | 1.35 |
| Maximum | 250.0 | 34.9% | 6.02 | 1.50 |

**Table 3. Sample Description by State (sorted in descending order by mean capacity factor)**

| State | # of Projects | Capacity ($MW_{AC}$) | Mean 2014 NCF | Mean 2014 GHI ($kWh/m^2/day$) | Mean ILR ($MW_{DC}/MW_{AC}$) | % Tracking |
|---|---|---|---|---|---|---|
| AZ | 19 | 594 | 30.4% | 5.62 | 1.27 | 89.5% |
| CA | 41 | 1,561 | 28.1% | 5.52 | 1.26 | 46.3% |
| NV | 8 | 284 | 27.9% | 5.41 | 1.23 | 50.0% |
| CO | 4 | 62 | 27.3% | 5.30 | 1.14 | 100.0% |
| NM | 13 | 154 | 26.9% | 5.63 | 1.17 | 61.5% |
| TX | 6 | 84 | 23.0% | 4.85 | 1.18 | 83.3% |
| GA | 3 | 54 | 22.5% | 4.65 | 1.27 | 0.0% |
| TN | 1 | 8 | 21.0% | 4.36 | 1.26 | 0.0% |
| NC | 3 | 54 | 20.9% | 4.26 | 1.21 | 66.7% |
| FL | 4 | 53 | 20.0% | 4.88 | 1.12 | 50.0% |
| DE | 2 | 22 | 19.9% | 3.94 | 1.19 | 50.0% |
| IN | 4 | 39 | 19.4% | 3.88 | 1.35 | 0.0% |
| MD | 3 | 39 | 19.2% | 3.90 | 1.27 | 0.0% |
| IL | 2 | 28 | 19.0% | 3.77 | 1.18 | 50.0% |
| NY | 1 | 32 | 18.5% | 3.93 | 1.20 | 0.0% |
| OH | 2 | 18 | 18.4% | 3.75 | 1.20 | 50.0% |
| NJ | 11 | 107 | 17.5% | 3.85 | 1.20 | 9.1% |
| PA | 1 | 10 | 15.9% | 3.76 | 1.15 | 0.0% |
| **Total US** | **128** | **3,201** | **25.5%** | **5.08** | **1.23** | **50.8%** |

***Tracking:*** Single- or dual-axis tracking devices that keep the plane of the array as perpendicular as possible to the sun's rays throughout the day and/or year boost performance relative to a fixed-tilt project. Previous simulation work found that single-axis tracking can boost performance relative to a fixed-tilt array by 12-25% (i.e., in percentage, rather than absolute, terms) depending on location, while the corresponding increase for dual-axis tracking is 30-45% [11]. Roughly half (50.8%) of the projects in our sample use single-axis tracking (Table 3, Figure 1), while the remaining projects have modules that are mounted at a fixed tilt and azimuth (i.e., there are no dual-axis tracking projects in our sample[13]). Single-axis tracking is more common in

[13] Despite the potential incremental increase in output relative to single-axis trackers, dual-axis trackers have not yet been deployed in the utility-scale sector to any great extent in the United States. This is due to a combination of cost and performance concerns (given a greater number of moving parts) plus the fact that the largest performance boost

southwestern states with a strong solar resource (Table 3), for several reasons: (1) the greater up-front cost and ongoing maintenance expense of tracking is more easily justified when tracking a stronger resource; (2) most single-axis trackers are installed horizontally (i.e., *not* tilted southward), which incurs less of a production penalty in lower latitudes where, in the United States, the sun is higher in the sky and the resource is also typically stronger; and (3) the Southwest still has expansive and relatively inexpensive tracts of land that can accommodate the greater land-area-per-MW requirements of tracking (to avoid shading).[14]

Figure 1 shows the distribution of capacity factors within our sample, broken out by fixed-tilt (dark/red bars) versus tracking projects (light/yellow bars), as well as in aggregate (shaded/orange bars).[15] The distribution is somewhat bi-modal, due to the influence of tracking on capacity factor. The 63 fixed-tilt projects in our sample range in capacity factor from 14.8-30.6%, with 19% being the most common bin, while the 65 tracking projects range in capacity factor from 18.5-34.9%, with 29% being the most common bin.

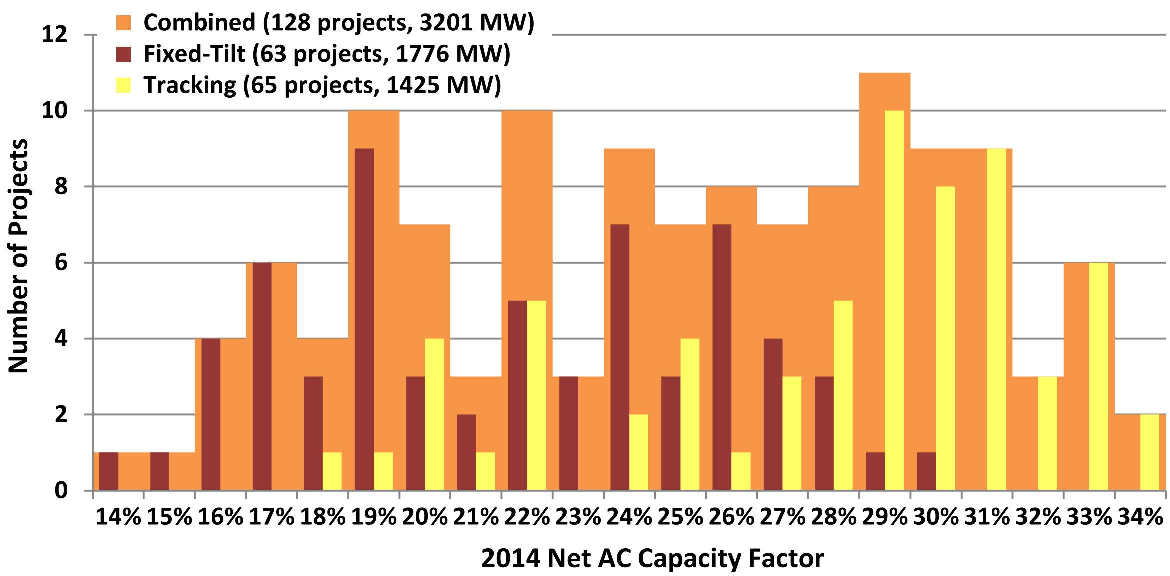


**Figure 1. Histogram of 2014 Net AC Capacity Factors within the Sample**

***Inverter loading ratio ("ILR"):*** Also sometimes referred to as the DC/AC ratio, array-to-inverter ratio, oversizing ratio, overloading ratio, or DC load ratio, the ILR is simply the ratio of a project's DC capacity rating (determined by the number and rated capacity of PV modules) to its AC capacity rating (determined by the maximum AC power output of the inverters). With the cost of PV modules having dropped precipitously in recent years, and more rapidly than the cost

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from dual-axis tracking occurs in more-northerly latitudes [11], which to date have seen only limited utility-scale PV deployment in the United States. That said, several Texas projects that achieved commercial operation in 2014 do use dual-axis tracking, and it will be interesting to track their performance in the future.

[14] Though not decipherable from Table 3, the mean 2014 GHI among the tracking projects in our sample is 5.33 kWh/m$^2$/day, compared to 4.83 kWh/m$^2$/day among the fixed-tilt projects.

[15] The project-level capacity factor data presented in Figure 1 and used in our regression analysis was originally compiled for [5] and originates from a combination of sources, including the Federal Energy Regulatory Commission's (FERC's) Electronic Quarterly Report filings, FERC Form 1 filings, the Energy Information Administration's (EIA's) Form EIA-923, and various state regulatory filings.

of inverters, many developers have found it economically advantageous to increase the DC capacity rating of the array relative to the AC capacity rating of the inverters. As this happens, the inverters operate closer to (or at) full capacity for a greater percentage of the day, which – like tracking – boosts the capacity factor,[16] at least in AC terms (this practice will actually *decrease* the capacity factor in DC terms, as some amount of power "clipping" may occur during peak production periods in high-insolation summer months[17]).

The ILRs in our project sample range from 1.05 to 1.50 with a median of 1.24 (Table 2) and a mean of 1.23 (Table 3). Though not shown in Tables 2 or 3, the fixed-tilt projects in our sample have a slightly higher mean ILR (1.25) than the tracking projects (1.21), which makes sense given that tracking and a high ILR are, at least to some extent, substitutes for one another in the sense that they both flatten the diurnal generation profile by boosting production during the morning and evening "shoulder" periods.

***Project vintage:*** Project vintage might be expected to play a role, with newer projects having higher capacity factors because the efficiency of PV modules has increased over time. As module efficiency increases, however, developers simply either use fewer modules to reach a desired amount of capacity (thereby saving on balance-of-system and land costs in addition to module costs), or they use the same number of modules to boost the amount of capacity installed on a fixed amount of land (which directly reduces at least $\$/W_{DC}$ costs, if not also $\$/W_{AC}$ costs). In other words, PV module efficiency improvements over time show up primarily as cost savings rather than as higher capacity factors. Project vintage is, nevertheless, important to our purpose given that PV module performance tends to degrade over time, on the order of 0.2% to 1%/year [15,16]. For this reason, we would expect older projects to have lower capacity factors than newer projects, all else equal.[18]

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[16] This is analogous to the boost in capacity factor achieved by a wind turbine when the size of the rotor increases relative to the turbine's nameplate capacity rating. This decline in "specific power" ($W/m^2$ of rotor swept area) causes the generator to operate closer to (or at) its peak rating more often, thereby increasing capacity factor.

[17] Power clipping, also known as power limiting, is comparable to spilling excess water over a dam (rather than running it through the hydropower turbines) or feathering a wind turbine blade to allow excess wind to slip by. In the case of solar, however, clipping occurs electronically rather than physically: as the DC input to the inverter approaches maximum capacity, the inverter moves away from the "maximum power point" so that the array operates less efficiently, resulting in lower DC power output [14]. In this sense, clipping is a bit of a misnomer, in that the inverter never really even "sees" the excess DC power; rather, it is simply not generated in the first place – only *potential* generation is lost. That said, it is important to recognize that PV module capacity ratings are based on standard test conditions ("STC") of 1,000 $W/m^2$ of irradiance at 25° C and an air mass of 1.5, and that actual operating conditions in the field are often less-advantageous (e.g., cell temperatures are often greater than 25° C), which limits the actual DC output to something less than STC-rated output. This limitation, in turn, reduces the amount of power clipping that occurs.

[18] Conversely, one might expect newer projects – and in particular those completed in late 2013 – to possibly exhibit *lower* 2014 capacity factors if they spent a portion of 2014 ironing out potential "teething issues" that can sometimes hamper initial production at new projects. Such teething issues have been particularly notable among several recent concentrating solar thermal power projects [5], and are also somewhat common in the wind power industry, though PV projects are perhaps less susceptible to such problems, due to having fewer moving parts. Though not presented in this paper, we did test for potential teething issues within our sample by including a dummy variable to represent projects that achieved commercial operation in 2013; the coefficient was extremely small and highly insignificant, leading us to ignore this possible driver.

***Tilt and azimuth:*** Especially for fixed-tilt projects, which make up 49.2% of our sample, PV module orientation will impact capacity factor. Unfortunately, we lack good data on the tilt and azimuth of the fixed-tilt projects in our sample. However, for the types of projects analyzed in this paper – i.e., ground-mounted utility-scale PV projects that can cost tens or hundreds of millions of dollars to build – we assume that these two fundamental parameters will always be optimized across projects to maximize revenue, and therefore would not add any incremental explanatory power to our models even if known and included (i.e., under this assumption of optimal orientation, the omission of tilt and azimuth should not detract from the models).[19] To date, given that most PPAs either do not vary pricing based on the time of delivery or else employ time-of-delivery pricing that favors mid-day generation [4,5], maximizing revenue has almost universally been achieved by maximizing annual energy production (i.e., capacity factor).

***Operating temperature and module power temperature coefficient:*** PV modules are less efficient at higher operating temperatures, though certain types or brands of modules are better able to handle the heat than others. For example, First Solar, which makes cadmium-telluride modules, claims that its modules (with a power temperature coefficient of -0.25%/°C) outperform typical crystalline silicon modules (with power temperature coefficients ranging from -0.3%/°C to -0.5%/°C) at operating temperatures in excess of 25°C [17]. Unfortunately, we do not have universally good information on module make and model, and hence temperature coefficient, within our project sample. Nor do we have reliable data on site-specific daytime operating temperatures.[20]

### *2.3 Selection of Independent Variables for the Regression Analysis*

Of the six potential drivers of 2014 capacity factors described above in Section 2.2, we included the first four – solar resource strength (GHI), tracking, ILR, and commercial operation year – as independent variables in the regression model and omitted the last two – tilt/azimuth and temperature – due to lack of sufficient, or sufficiently high-quality, data (and in the case of tilt/azimuth, also a presumption of little relevant differentiation among this sample).

Figure 2 presents our sample's 2014 net capacity factors broken out among three of these four independent variables (commercial operation year is excluded). The columns show the mean 2014 NCF within each bin, while the circle markers show 2014 NCFs for each individual project. In order to ensure an even distribution of projects among bins, the width of the GHI and

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[19] This is one important reason why utility-scale projects are more amenable to this type of empirical capacity factor analysis than are residential and commercial systems, which must often contend with sub-optimal roof orientation and/or partial shading – factors that that are difficult to ascertain remotely. Another reason that we focus on the utility-scale sector is that performance data are much more readily available for utility-scale projects (e.g., from the sources listed in footnote 15) than for residential and commercial projects.

[20] We did attempt to include a rather crude proxy for operating temperature – i.e., the long-term annual mean of maximum monthly temperatures at the approximate project location – within our regression model, but the coefficient was highly insignificant and its sign was the opposite of expectations (perhaps due to the likely correlation between temperature and GHI), prompting us to abandon this variable. Similarly, we attempted to approximate the effect of power temperature coefficient by comparing the performance of projects using cadmium-telluride and silicon modules (given cadmium-telluride's lower power temperature coefficient), but the results were inconclusive, perhaps because we are unable to account for potentially just-as-large differences in power temperature coefficient among different types or brands of silicon modules (which are used by 77% of the projects and 62% of the capacity in our sample).

ILR bins are based on the 33rd and 66th percentile values for each. Though several bins include only two or three projects (and one has no projects at all), in general a positive relationship between net capacity factor and ILR, tracking, and GHI is evident, particularly among the mean values (there is, naturally, more variability among the individual projects).

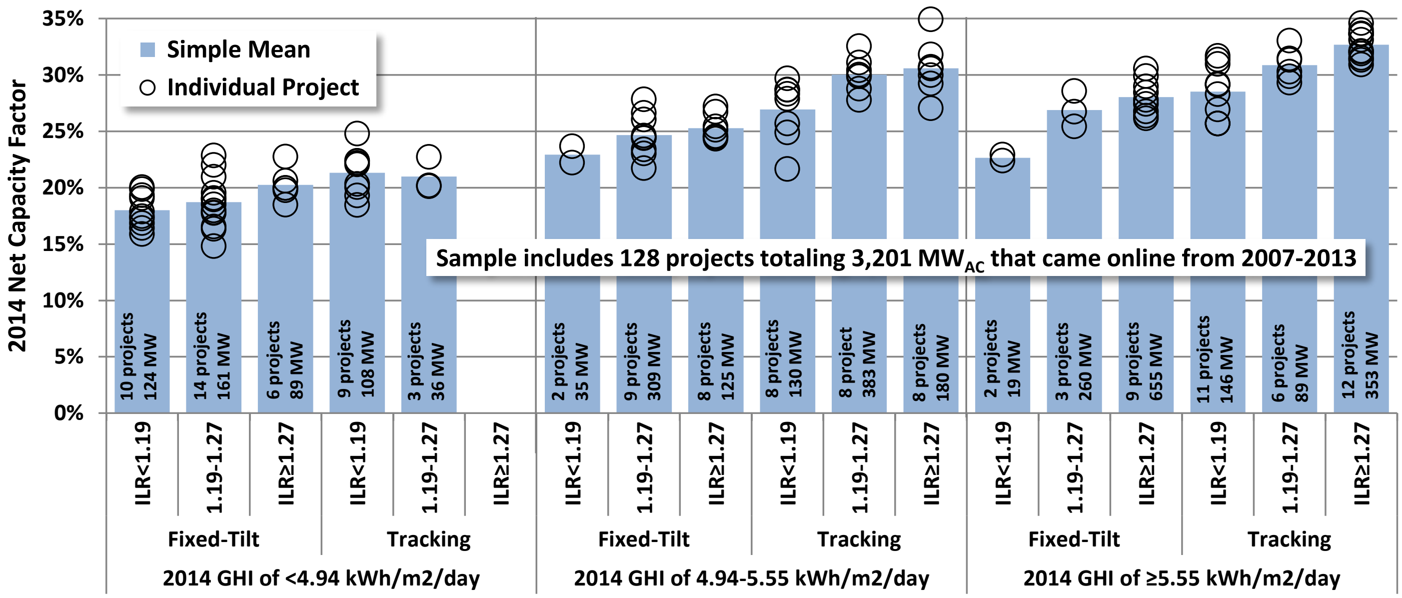


**Figure 2. 2014 Net AC Capacity Factor by Resource Strength, Fixed-Tilt vs. Tracking, and Inverter Loading Ratio**

We also included three "interactive" variables in the regression analysis to try to capture the nuances in how GHI, tracking, and ILR influence capacity factor in relation to one another.[21] For example, we would expect single-axis tracking to provide a greater boost to capacity factor at sites with a stronger solar resource, and so interacted tracking with GHI to try and isolate that relationship.[22] Similarly, given that tracking and a high ILR can, to some extent, be thought of as substitutes for one another, we would expect the benefit of tracking to diminish at higher ILRs, and so interacted tracking with ILR to analyze this tradeoff. Finally, as with tracking, we would

[21] Unlike with GHI, tracking, and ILR, there is relatively little intuition for interacting our fourth independent variable – commercial operation year – with any of the other three. Nevertheless, we did try including a variable that interacted commercial operation year with tracking, on the possibility that tracking technology may have improved sufficiently over the timeframe of our sample to have a discernible impact on capacity factor among different project vintages. The coefficient, however, was extremely small and highly insignificant, leading us to not include it in the final models.

[22] This interaction between tracking and GHI is somewhat of a simplification and approximation, as the NCF benefit of single-axis tracking is more accurately driven by the amount of direct normal irradiance or DNI (a component of GHI, along with diffuse horizontal irradiance) at any given location, along with latitude (e.g., all else equal, horizontal-mounted single-axis tracking projects will perform better at lower latitudes where the sun is higher in the sky) [11]. We did try adding both a long-term (as opposed to 2014) measure of DNI and latitude to the regression model and interacting them both with tracking (in lieu of interacting tracking with GHI), but the results were counterintuitive, and adding these variables introduced heteroskedacity and multicollinearity problems (presumably due to the strong correlation between DNI and GHI). To avoid these issues, we chose to stick with the simpler model that interacts 2014 GHI with tracking (i.e., avoiding the addition of DNI and latitude), even if this specification is somewhat imperfect.

also expect higher ILRs to provide a greater NCF boost at sites with a stronger solar resource, and so interacted ILR with GHI to examine this relationship.

The next section quantifies these individual and interactive relationships through multiple regression analysis.

## 3. Model Specification and Results

The four individual (i.e., non-interactive) independent variables included in the regression model are solar resource strength (GHI), tracking vs. fixed-tilt (a dummy variable), ILR, and commercial operation year. An examination of the two continuous independent variables – resource strength (GHI) and ILR – suggested that the ILR variable should be transformed by taking its natural logarithm. This transformation makes intuitive sense in that it reflects the diminishing marginal benefit of increasing the ILR at higher levels, due to the resulting increase in power clipping. Additionally, to ease interpretation of results and to guard against multicollinearity, we centered our independent variables (except for the tracking dummy variable) by either subtracting their means (in the case of the two continuous variables) or by subtracting 2007 (in the case of the commercial operation year variable).[23]

Table 4 presents a buildup of the regression model, starting with just a single independent variable – 2014 GHI – in Model 1, and then adding each additional independent variable (as well as the three interactive variables) to progress to our preferred model specification in Model 5. The $R^2$ of Model 1 shows that 2014 GHI alone predicts 71.6% of the variance in 2014 net capacity factor.[24] The constant value of 0.2546 means that at the average 2014 GHI value among our sample (from Table 3, 5.08 kWh/m$^2$/day), the projected capacity factor is 25.46%. The coefficient of the 2014 GHI variable means that for each 1 kWh/m$^2$/day increase in GHI, the model would expect capacity factor to increase by 6.04% (in absolute rather than percentage terms, so from 25.46% at the mean to 31.50% for a GHI of 6.08 kWh/m$^2$/day – which is slightly above the maximum 2014 GHI among our sample). Both the 2014 GHI variable and the constant term are highly statistically significant ($p<0.01$).

Model 2 adds the Tracking dummy variable, which increases the $R^2$ to 0.811. The constant term finds that at the average value for 2014 GHI, the projected capacity factor for a *fixed-tilt* project is 23.75%. Adding single-axis tracking would increase capacity factor by 3.37% (to 27.12%), and a 1 kWh/m$^2$/day increase in 2014 GHI would increase capacity factor by 5.21% (to 28.96% and 32.33% for a fixed-tilt and tracking project, respectively). Both independent variables and the constant term are highly significant ($p<0.01$).

[23] Because the independent variables are centered, the constant terms in Table 4 can be easily interpreted as the 2014 NCF of a fixed-tilt project (for Models 2-5 that include the Tracking dummy variable) built in 2007 (for Models 4 and 5 that include the COD Year variable) at the mean values of all other independent variables.

[24] Though not shown in Table 4, we also regressed each of the other three non-interactive independent variables individually against 2014 net capacity factor, to get a sense for their relative individual explanatory power. The resulting $R^2$ for each individual variable is as follows: 0.716 for 2014 GHI, 0.345 for Tracking, 0.098 for ln(ILR), and 0.065 for COD Year. When building up to Models 4 and 5 in Table 4, we added each of these variables in the descending order of their individual $R^2$.

**Table 4. Model Buildup and Robust Results**[25]

***In all five models, the dependent variable is net AC capacity factor in 2014.***

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| **2014 GHI** | 0.0604*** | 0.0521*** | 0.0478*** | 0.0479*** | 0.0423*** |
| | (0.00280) | (0.00265) | (0.00199) | (0.00202) | (0.00245) |
| **Tracking** | | 0.0337*** | 0.0429*** | 0.0421*** | 0.0405*** |
| | | (0.00443) | (0.00296) | (0.00303) | (0.00285) |
| **ln(ILR)** | | | 0.2391*** | 0.2146*** | 0.2158*** |
| | | | (0.01911) | (0.02206) | (0.03393) |
| **COD Year** | | | | 0.0033** | 0.0023* |
| | | | | (0.00138) | (0.00132) |
| **Tracking x 2014 GHI** | | | | | 0.0186*** |
| | | | | | (0.00501) |
| **Tracking x ln(ILR)** | | | | | -0.0015 |
| | | | | | (0.04686) |
| **2014 GHI x ln(ILR)** | | | | | 0.0575* |
| | | | | | (0.02952) |
| **Constant** | 0.2546*** | 0.2375*** | 0.2328*** | 0.2172*** | 0.2202*** |
| | (0.00243) | (0.00268) | (0.00198) | (0.00640) | (0.00598) |
| **Observations** | 128 | 128 | 128 | 128 | 128 |
| **$R^2$** | 0.716 | 0.811 | 0.920 | 0.926 | 0.938 |
| **Root MSE** | 0.02746 | 0.02248 | 0.01467 | 0.01423 | 0.01316 |

Robust standard errors are in parentheses, below the coefficients

***p<0.01, **p<0.05, *p<0.1

All continuous variables are centered around their means. The COD Year variable is based in the earliest possible year, 2007.

Interpretation of Models 3 and 4 becomes more involved due to the presence of multiple continuous variables, and so will be bypassed in favor of spending more time on the similar, but more-complete, Model 5. Suffice it to say that adding the natural logarithm of ILR ("ln(ILR)") in Model 3 boosts the $R^2$ to 0.920, while adding the commercial operation year ("COD Year") in Model 4 pushes the $R^2$ only slightly higher to 0.926. With the exception of "COD Year" in Model 4 (for which $p<0.05$), all other independent variables and constant terms in both Model 3 and Model 4 are highly significant ($p<0.01$).

Given the strong statistical significance of all variables and constant terms in Models 1-4, along with the relative stability in the coefficients, robust standard errors, and constant terms across models as each new independent variable is added, Model 5 introduces the three additional "interactive" variables that seek to capture the nuances in how GHI, tracking, and ILR influence capacity factor in relation to one another. Two of these three interactive variables are statistically significant (Tracking x 2014 GHI at the 1% significance level, 2014 GHI x ln(ILR) at the 10%

[25] Although our data do not appear to have heteroscedasticity problems, we nevertheless took the precaution of running "robust" regressions that correct the standard errors using Huber-White sandwich estimators.

significance level), while the third (Tracking x ln(ILR)) is not significant. However, three "partial F" tests of (1) all three variables (one individual, two interactive) that involve 2014 GHI, (2) all three variables that involve Tracking, and (3) all three variables that involve ln(ILR) find high statistical significance in all three cases. The $R^2$ of Model 5 increases only slightly with the addition of these three interactive variables, to 0.938, while the COD Year variable is now only significant at the 10% level (compared to significance at the 5% level in Model 4).

Figure 3 plots the fitted 2014 NCF estimates resulting from Model 5 against the actual empirical values (along with a best fit line).[26] The relationship appears to be highly linear, and the relatively small differences between estimated and actual NCFs visually support the high adjusted $R^2$ values reported in Table 4.[27]

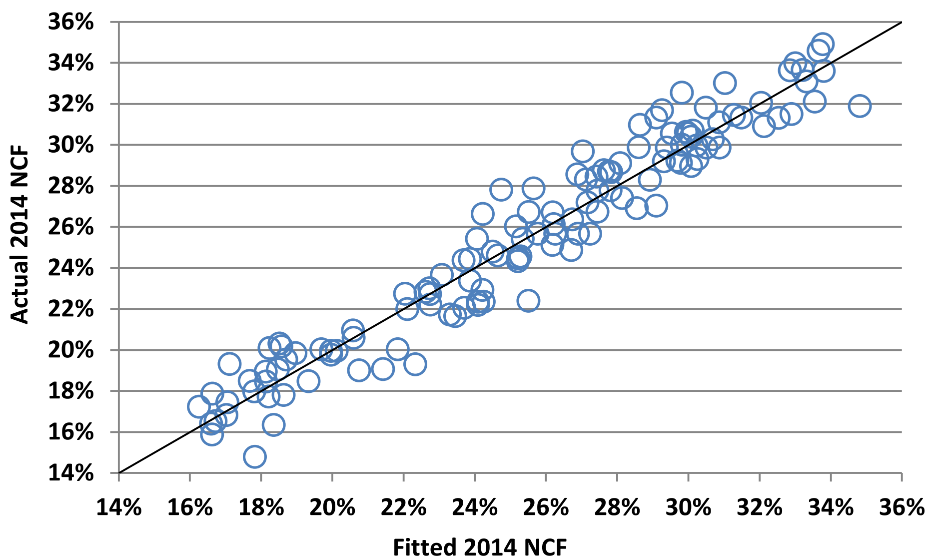


**Figure 3. Scatter Plot of Model 5 Fitted versus Actual 2014 NCF**

Model 5 predicts that a fixed-tilt project built in 2007 with average 2014 GHI and ILR will have a 2014 NCF of 22.02%. Single-axis tracking adds 4.05% to this same project's 2014 NCF, for 26.07% in total.[28] Each successive COD Year adds 0.23% to both fixed-tilt and tracking projects, such that a 22.02% and 26.07% NCF for a fixed-tilt and tracking project, respectively, built in 2007 becomes 23.41% and 27.46% for projects built in 2013. Said another way, Model 5 predicts that older/earlier projects have lower 2014 capacity factors to the tune of 0.23%/year on average; one possible interpretation is that this coefficient is detecting module degradation

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[26] The full equation for Model 5 is as follows: 2014 NCF = .0423*(2014 GHI-mean(2014 GHI)) + 0.0405*(1 if Tracking, 0 if Fixed-Tilt) + 0.2158*(ln(ILR)-mean(ln(ILR)) + 0.0023*(COD Year-2007) + 0.0186*(1 if Tracking, 0 if Fixed-Tilt)*(2014 GHI-mean(2014 GHI)) + -0.0015*(1 if Tracking, 0 if Fixed-Tilt)*(ln(ILR)-mean(ln(ILR)) + 0.0575*(2014 GHI-mean(2014 GHI))*(ln(ILR)-mean(ln(ILR)) + 0.2202.

[27] In addition to using robust regression techniques and plotting and visually inspecting the residuals from Figure 3 and Model 5, we also conducted several statistical tests to ensure that our data and model specification conform to the underlying assumptions of OLS regression. The Breusch-Pagan and White tests both indicate that there is no heteroscedasticity problem in the error term, the Shapiro-Wilk test indicates normality in the residuals, the Variance Inflator Factor test suggests no multicollinearity problems, and the linktest finds good model specification.

[28] In percentage terms, this 18.4% empirical boost in 2014 NCF is right in the middle of the 12-25% range predicted by earlier simulations [11].

rates.[29] Figure 4 shows the progression of 2014 NCF by project vintage (assuming average GHI and ILR) for both fixed-tilt (solid line) and tracking (dashed line) projects, along with the benefit of tracking (shaded area), which in this case is constant at 4.05% across project vintages given that we chose not to interact Tracking with COD Year (as explained earlier in footnote 21).

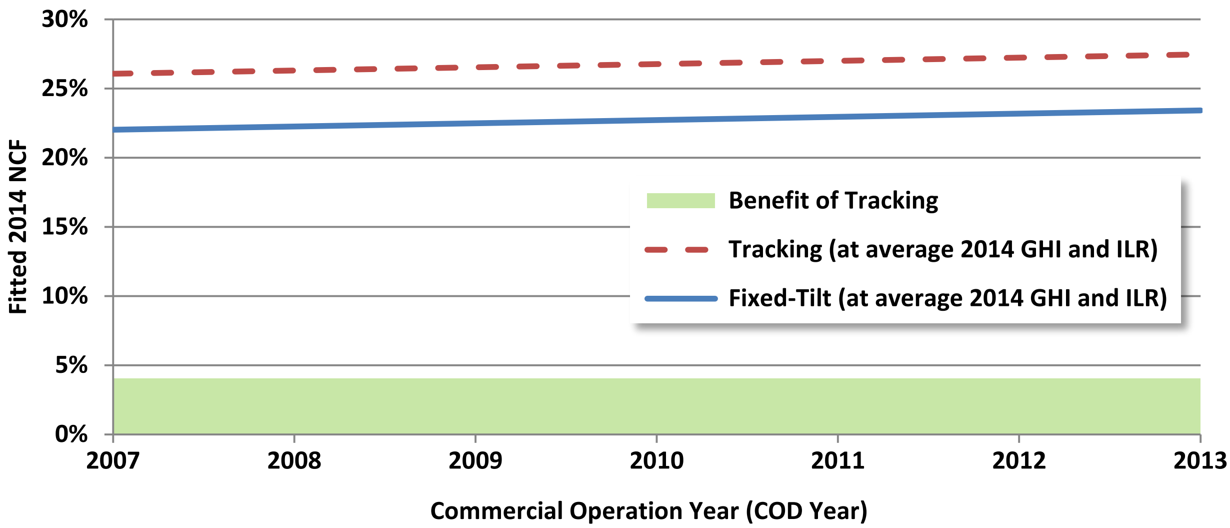


**Figure 4. Impact of COD Year at Average 2014 GHI and ILR**

Given our natural interest in newer rather than older projects, and the need to fix the COD Year in order to more-easily interpret the influence of other variables, the rest of the Model 5 interpretation focuses on projects that achieved commercial operation in 2013. Figure 5 shows the impact of 2014 GHI on a 2013 project with an average ILR. For each 1 kWh/m$^2$/day change in 2014 GHI, the model predicts a linear 4.23% absolute change in 2014 NCF for a fixed-tilt project and a 6.08% absolute change in 2014 NCF for a tracking project.[30] This means that the benefit of tracking increases at sites with a stronger solar resource, which makes intuitive sense and is consistent with the greater prevalence of tracking at high-GHI sites seen in Section 2.2, Table 3, and footnote 12.[31]

[29] An average module degradation rate of 0.23%/year would fall towards the low end of the range of empirical degradation rates previously observed [16], and would be even slightly below the low end of the 0.25%-1.0% range of projected degradation rates found within a sample of 29 utility-scale PV PPAs totaling 3,215 MW$_{AC}$ (with a sample mean degradation rate of 0.6% and a median of 0.5%) [5]. That said, SunPower, which has manufactured a significant percentage of the modules used in utility-scale projects in the United States (including 12% of the projects and 15% of the capacity in our project sample) claims that its degradation rates are less than 0.25%/year [15], and has backed up that assertion by promising degradation rates as low as 0.25% in two PPAs within the aforementioned PPA sample.

[30] The effect of GHI on a fixed-tilt project is simply the *2014 GHI* coefficient of 0.0423. For a tracking project, simply add the *Tracking x 2014 GHI* coefficient of 0.0186 to reach 0.0608 in total.

[31] In percentage terms, the benefit of tracking is 10.8% at a 2014 GHI of 4.0 and 22.7% at a 2014 GHI of 6.0 – similar to the 12%-25% range predicted by earlier simulations [11].

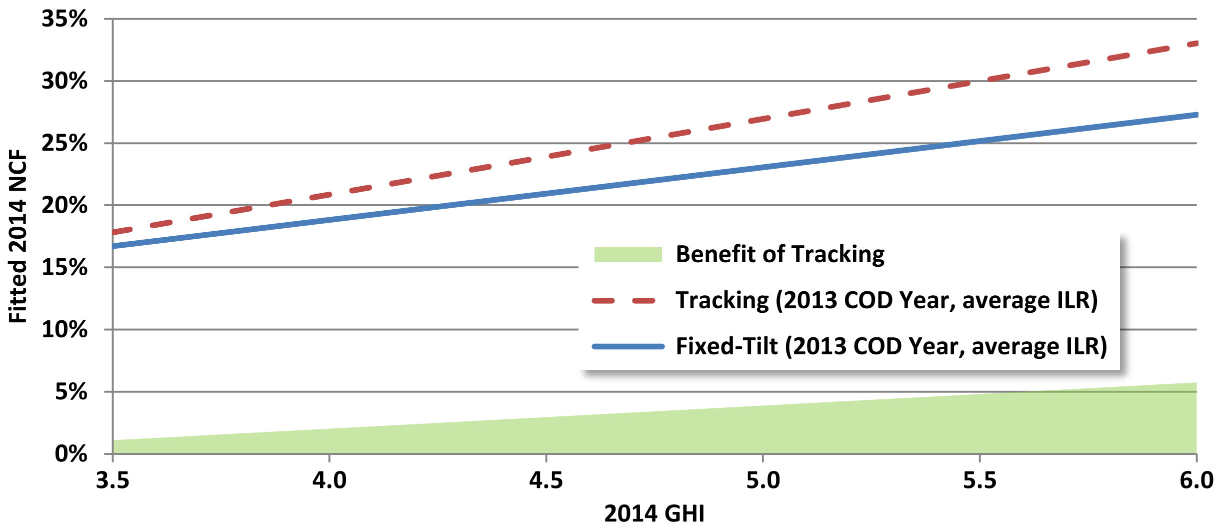


**Figure 5. Impact of 2014 GHI for 2013 COD Year and Average ILR**

Conversely, Figure 6 shows the impact of ILR (transformed back from the natural logarithm) on a 2013 project with an average 2014 GHI. As shown by the slight deviation from the linear dashed lines (included only for visual comparison), due to its logarithmic specification, ILR has a slightly diminishing marginal effect on 2014 NCF as it increases. For example, for both fixed-tilt and tracking projects, 2014 NCF increases by 1.00% when moving from an ILR of 1.05 to 1.10, but by only 0.73% when moving from an ILR of 1.45 to 1.50. This diminishing effect potentially reflects greater amounts of power clipping at higher ILRs. As shown earlier in Table 2, however, 90% of the projects in our sample have ILRs of 1.35 or less – levels at which significant power clipping is unlikely to occur.

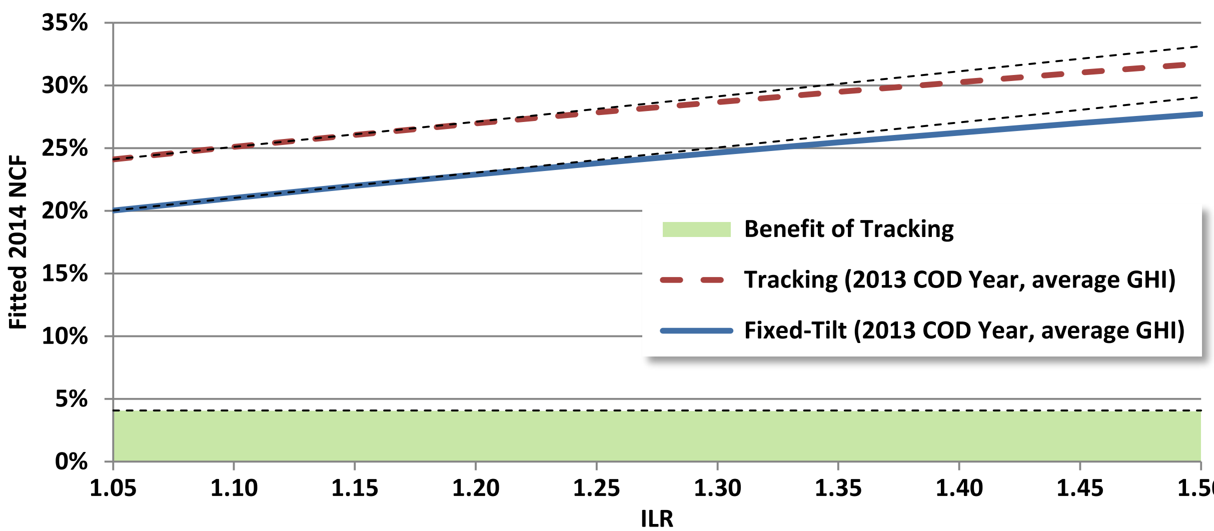


**Figure 6. Impact of ILR for 2013 COD Year and Average 2014 GHI**

Similarly, though hard to see in Figure 6, the positive influence of tracking also diminishes ever so slightly at higher ILRs (again, due to its logarithmic specification) – e.g., from 4.07% at an ILR of 1.05 to 4.02% at an ILR of 1.50. This deterioration makes intuitive sense (though the small magnitude is somewhat surprising, and as noted earlier, this effect is not statistically significant), given that boosting the ILR has a similar effect as tracking in terms of flattening the diurnal generation profile by increasing generation during the morning and evening shoulder periods. In other words, if a project's diurnal generation profile is already fairly flat due to a high ILR, then the incremental ability of tracking to increase generation during the shoulder periods should be reduced.

Lastly, Table 5 demonstrates the changing effect of ILR at different GHI levels and vice versa, for both fixed-tilt and tracking projects. The two shaded rows labeled "(A)" show the difference in fitted 2014 NCF between one project with an ILR of 1.45 and another with an ILR of 1.10 at different levels of GHI. The NCF benefit of a higher ILR increases at higher GHI levels, simply because there is more available insolation that can be captured by boosting the ILR. Moreover, for any given GHI, the benefit of a higher ILR is slightly greater for fixed-tilt than for tracking projects (e.g., 4.24% vs. 4.20% for a GHI of 4.0), which also makes intuitive sense given that tracking is somewhat redundant with a high ILR.

Similarly, the two shaded columns labeled "(B)" in Table 5 show the difference in fitted 2014 NCF between one project with an average 2014 GHI of 5.5 kWh/m$^2$/day and another with 4.0 kWh/m$^2$/day at different ILRs. The NCF benefit of a higher GHI increases with higher ILRs, as the latter is better able to capture the former. Moreover, for any given ILR, the benefit of a higher GHI is greater for tracking than for fixed-tilt projects (e.g., 8.9% vs. 6.1% for an ILR of 1.20), as tracking is able to capitalize on the stronger solar resource.

Finally, the bottom third of Table 5 confirms earlier findings from Figures 5 and 6 above: for a given ILR, the benefit of tracking increases with GHI (given a greater resource to capture through tracking); conversely, for a given GHI, the benefit of tracking *decreases* slightly as ILR increases (again, given that tracking is somewhat redundant with a high ILR).

As a way to graphically summarize the interpretation of Model 5, Figure 7 shows the individual and combined effects of the regressors in waterfall format. It begins at the far left with the constant term of 22.02%, which represents the predicted 2014 net capacity factor from a 2007 fixed-tilt project with average GHI (5.08 kWh/m$^2$/day) and ILR (1.23). It then adds the impact of each of the four non-tracking-related regressors until arriving, in the middle of the graph, at a 2013 fixed-tilt project with a GHI of 6.08 kWh/m$^2$/day and an ILR of 1.33, which has a predicted 2014 net capacity factor of 29.78%. The three tracking-related regressors are then added in turn to reach, on the far right of Figure 7, a predicted 2014 net capacity factor of 35.68% for a 2013 tracking project with the same GHI (6.08) and ILR (1.33) levels.

**Table 5. Primary and Interactive Effects of GHI, ILR, and Tracking on Fitted 2014 NCF**

*Fitted 2014 NCF of a Fixed-Tilt Project with a 2013 COD*

| | ILR\GHI | 3.5 | 4.0 | 4.5 | 5.0 | 5.5 | 6.0 | *(B) 5.5-4.0* |
|---|---|---|---|---|---|---|---|---|
| | 1.05 | 14.8% | 16.4% | 18.1% | 19.7% | 21.4% | 23.1% | *5.0%* |
| | 1.10 | 15.3% | 17.1% | 18.9% | 20.7% | 22.5% | 24.3% | *5.4%* |
| | 1.15 | 15.9% | 17.8% | 19.7% | 21.7% | 23.6% | 25.5% | *5.8%* |
| | 1.20 | 16.4% | 18.5% | 20.5% | 22.6% | 24.6% | 26.7% | *6.1%* |
| | 1.25 | 16.9% | 19.1% | 21.3% | 23.4% | 25.6% | 27.8% | *6.5%* |
| | 1.30 | 17.4% | 19.7% | 22.0% | 24.3% | 26.5% | 28.8% | *6.8%* |
| | 1.35 | 17.9% | 20.3% | 22.7% | 25.0% | 27.4% | 29.8% | *7.2%* |
| | 1.40 | 18.4% | 20.8% | 23.3% | 25.8% | 28.3% | 30.8% | *7.5%* |
| | 1.45 | 18.8% | 21.4% | 24.0% | 26.6% | 29.1% | 31.7% | *7.8%* |
| | 1.50 | 19.2% | 21.9% | 24.6% | 27.3% | 30.0% | 32.6% | *8.1%* |
| *(A)* | *1.45-1.10* | *3.44%* | *4.24%* | *5.03%* | *5.83%* | *6.62%* | *7.42%* | |

*Fitted 2014 NCF of a Tracking Project with a 2013 COD*

| | ILR\GHI | 3.5 | 4.0 | 4.5 | 5.0 | 5.5 | 6.0 | *(B) 5.5-4.0* |
|---|---|---|---|---|---|---|---|---|
| | 1.05 | 15.9% | 18.5% | 21.1% | 23.7% | 26.3% | 28.8% | *7.8%* |
| | 1.10 | 16.5% | 19.2% | 21.9% | 24.6% | 27.4% | 30.1% | *8.2%* |
| | 1.15 | 17.0% | 19.9% | 22.7% | 25.6% | 28.4% | 31.3% | *8.6%* |
| | 1.20 | 17.5% | 20.5% | 23.5% | 26.5% | 29.4% | 32.4% | *8.9%* |
| | 1.25 | 18.0% | 21.1% | 24.2% | 27.3% | 30.4% | 33.5% | *9.3%* |
| | 1.30 | 18.5% | 21.7% | 24.9% | 28.1% | 31.3% | 34.5% | *9.6%* |
| | 1.35 | 19.0% | 22.3% | 25.6% | 28.9% | 32.2% | 35.6% | *9.9%* |
| | 1.40 | 19.4% | 22.9% | 26.3% | 29.7% | 33.1% | 36.5% | *10.3%* |
| | 1.45 | 19.9% | 23.4% | 26.9% | 30.4% | 33.9% | 37.5% | *10.6%* |
| | 1.50 | 20.3% | 23.9% | 27.5% | 31.1% | 34.8% | 38.4% | *10.8%* |
| *(A)* | *1.45-1.10* | *3.40%* | *4.20%* | *4.99%* | *5.79%* | *6.58%* | *7.37%* | |

*Benefit of Tracking for a Project with a 2013 COD*

| ILR\GHI | 3.5 | 4.0 | 4.5 | 5.0 | 5.5 | 6.0 |
|---|---|---|---|---|---|---|
| 1.05 | 1.13% | 2.06% | 2.99% | 3.91% | 4.84% | 5.77% |
| 1.10 | 1.12% | 2.05% | 2.98% | 3.91% | 4.84% | 5.77% |
| 1.15 | 1.11% | 2.04% | 2.97% | 3.90% | 4.83% | 5.76% |
| 1.20 | 1.11% | 2.04% | 2.97% | 3.90% | 4.82% | 5.75% |
| 1.25 | 1.10% | 2.03% | 2.96% | 3.89% | 4.82% | 5.75% |
| 1.30 | 1.10% | 2.02% | 2.95% | 3.88% | 4.81% | 5.74% |
| 1.35 | 1.09% | 2.02% | 2.95% | 3.88% | 4.81% | 5.74% |
| 1.40 | 1.08% | 2.01% | 2.94% | 3.87% | 4.80% | 5.73% |
| 1.45 | 1.08% | 2.01% | 2.94% | 3.87% | 4.80% | 5.73% |
| 1.50 | 1.07% | 2.00% | 2.93% | 3.86% | 4.79% | 5.72% |

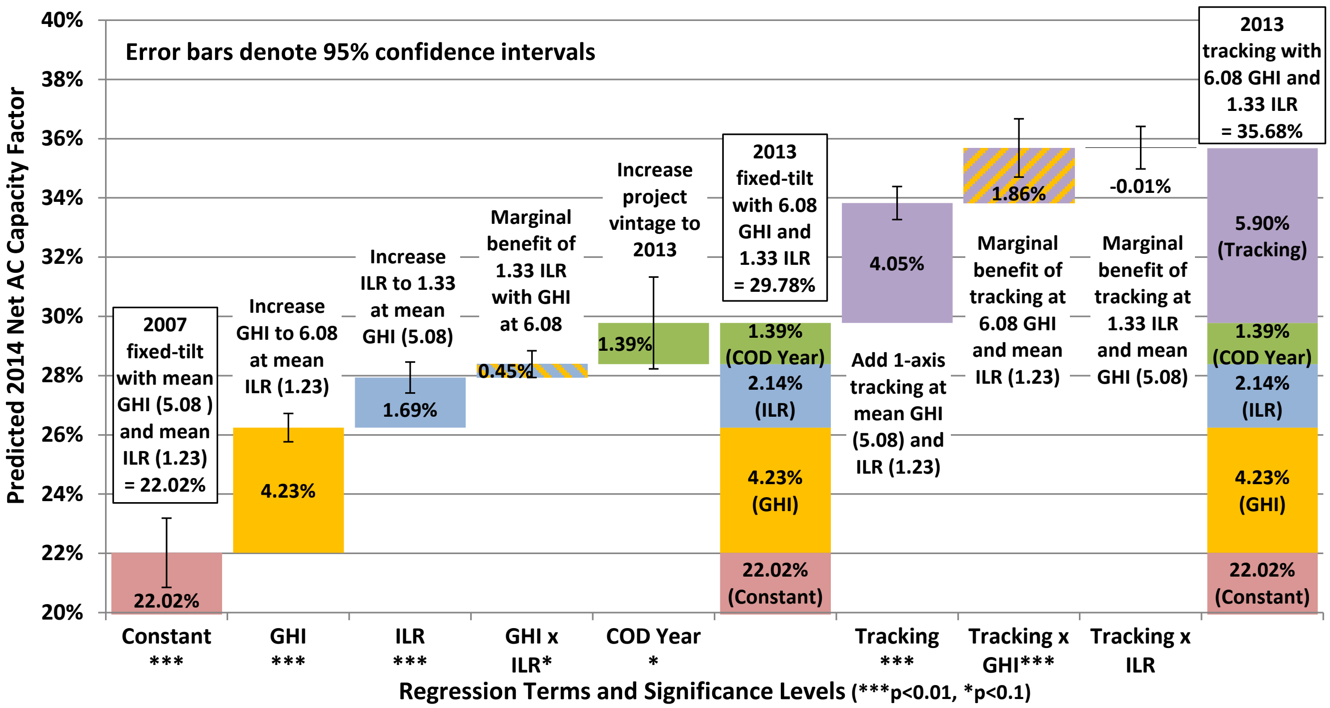


**Figure 7. Individual and Combined Effects of Model 5 Regression Terms**

## 4. Conclusions

The rapid ascendency of utility-scale PV in the United States over the last few years has resulted in a diverse fleet of operating projects that exhibit significant variation in empirical AC capacity factors, with the highest and lowest capacity factors in our sample differing by more than a factor of two. The regression models developed for this analysis find that just three highly significant independent variables – GHI, Tracking, and ILR – can explain 92% of this variation (see Model 3 in Table 4), with GHI alone able to explain 71.6% (see Model 1 in Table 4). That said, adding COD Year (in Model 4) and three interactive variables (in Model 5) improves the model further and reveals interesting relationships between these independent variables, without over-specifying the model.

Of the two additional potential drivers that were discussed in Section 2.2 but were omitted from the model due to insufficient data – i.e., the effect of module orientation (tilt and azimuth) and temperature (power temperature coefficient and module operating temperature) on performance – temperature is likely the more significant gap. Module orientation is primarily of relevance to only about half of the projects in our sample (i.e., the fixed-tilt projects), and it is highly likely that ground-mounted, fixed-tilt projects of this size and cost are almost universally oriented to maximize generation (and hence net AC capacity factor) at each site, thereby not adding much explanatory power to the model. The model would, however, presumably be improved with good data on power temperature coefficients and module operating temperatures.[32]

[32] Module operating temperature may, however, be correlated with GHI to some extent, in which case perhaps power temperature coefficient may be the more important of these two variables. That said, as noted earlier, we did attempt to approximate the effect of power temperature coefficient by comparing the performance of projects using

Taken together, the empirical data and statistical modeling results presented in this paper can provide a useful indication of the level of performance that solar project developers and investors can expect from various project configurations in different parts of the country. Moreover, although this paper has not attempted to compare ex-post to published ex-ante capacity factor projections, the tight relationship between fitted and actual capacity factors (for example, see Figure 3) should nevertheless instill confidence among investors that the projects in this sample, at least, have largely performed as expected.

Looking ahead, the analysis presented in this paper suggests that there is still room for utility-scale PV project capacity factors to progress further. For example, even within the confines of our sample and Model 5's specification, Table 5 suggest that the NCF of tracking projects at the highest limits of the GHI and ILR ranges could potentially move a little higher (e.g., as high as 38.4%) than the maximum empirical 2014 NCF in our sample of 34.9%. Moving beyond our sample and Model 5, progress towards even higher net capacity factors could – if economically warranted[33] – come from several different directions:

- First, ILRs could possibly move higher than the 1.50 maximum seen in our sample, as some inverters are designed to handle ILRs as high as 1.75 [18]. The extent to which ILRs will continue to move higher in the future depends in large part on the relative pricing of modules and inverters (and perhaps even trackers) going forward, which – in combination with PPA terms – determines the optimal ILR from an economic perspective. Even so, our analysis finds diminishing marginal returns to higher ILRs.
- Second, dual-axis tracking would boost net capacity factor beyond the levels achieved by the single-axis trackers in our sample. Although no utility-scale (i.e., >5 $MW_{AC}$) PV projects using dual-axis tracking had been built in the United States through 2013, several such projects came online during 2014, with 2015 being their first full year of operation. Adding these projects to the sample would be one way to refresh this analysis and perhaps improve the model.
- Third, although insolation is dictated by weather patterns and natural events and cannot be directly influenced with ease, it is, of course, possible to concentrate the strength of the sun's energy to boost generation. To date, most commercial concentrating photovoltaic ("CPV") projects have focused on minimizing the size of the solar cell in order to save on materials

cadmium-telluride and silicon modules (given cadmium-telluride's claimed advantage in this area), but the results were inconclusive, perhaps because we are unable to account for potentially just-as-large differences in power temperature coefficient among different types or brands of silicon modules (which are used by 77% of the projects and 62% of the capacity in our sample).

[33] Though each of the three approaches described below could boost capacity factors in the future, the extent to which any of these are implemented will depend in large part on whether it is economically advantageous to do so. At present, for example, the economics of utility-scale PV in the United States generally do not favor any of these three approaches, though this could change in the future. In fact, depending on how module and inverter prices, as well as PPA terms, play out going forward, one could even envision a future that economically favors a *lower* ILR than we see today, in which case capacity factors would presumably move lower as a result. Analyzing how these economic considerations interact with the empirical technical parameters reviewed herein is beyond the scope of this paper, but is fertile ground for future work.

costs, thereby tempering the benefit of concentration on capacity factor.[34] But this need not be the case going forward, particularly if the price of solar-grade silicon remains low.

Finally, the advent of project-level energy storage – still rare in the utility-scale PV market within the United States (and not reflected at all within our project sample) – will likely change how utility-scale PV project developers think about capacity factor and its relative importance. Maximizing generation (e.g., through tracking and/or array oversizing) to take better advantage of available transmission capacity over more of the day, or alternatively merely shifting generation from lower- to higher-priced periods, are just two possible responses. Whatever the optimal strategy (which could differ depending on a variety of factors, including PPA terms), this paradigm shift will, no doubt, complicate future analyses of comparative PV project performance.

[34] In fact, to date, the two largest CPV projects in the United States have performed at capacity factors well below what one would have expected from a similarly sited PV project using single-axis (as opposed to CPV's dual-axis) tracking [5]. SunPower's new C7 technology (which concentrates the sun's energy just seven times, compared to the hundreds of times achieved by other CPV technologies) is just now starting to be deployed, and time will tell whether this low-concentration approach yields better results than earlier high-concentration technology.

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